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**The Economics of Hospital Investment in Neonatal Intensive Care**

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# The Economics of Hospital Investment in Neonatal Intensive Care

**by**

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Dedicated to Bruce, Barbara, Ashley, Imelda and Diego.

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## The Economics of Hospital Investment in Neonatal Intensive Care

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In my first chapter, I estimate a dynamic model of hospital investments in neonatal intensive care in Texas. Since the early 1990s, investment in this service has been quite robust. Urban areas have multiple hospitals that offer high level facilities but generally operate below capacity. Quality in neonatal intensive care increases with the number of patients treated: higher patient volumes lead to lower mortality rates. The entry of additional neonatal intensive care units imposes a negative production externality on existing units by reducing patient volumes. I estimate a static model of patient demand to determine how patient choices respond to investment. Through the dynamic model I recover the hospitals' costs for treating different types of patients. I estimate a model of volume-outcome effects to predict how patient flows affect aggregate mortality. I simulate counterfactual outcomes under several restricted-entry regimes and find that up to 20% of the deaths of very low birth weight infants would be prevented in Texas by restricting entry of new neonatal intensive care units.

In my second chapter, I study an economy of scale in the production of quality and the consequences for consumer welfare in the context of neonatal intensive care in Texas. Using

detailed birth-certificate-level data including ID of the hospital of birth covering all NICU patients over eight years, I identify the causal effect of prior patient volume on the probability of mortality for new patients. I also empirically estimate a forgetting rate, capturing the rate at which the stock of accumulated experience declines in importance to the production of lower mortality. I find a very high rate of forgetting in this setting, suggesting that entry into this market may be quite harmful. I find that moving patients from low to high volume NICU's within each county in the state would lead to substantial savings in lives: on the order of 145 infants annually. Valuing these lives at $7,000,000 each results in a welfare improvement of $1,000,000,000. I propose some policy options for the regulator in light of my results, including direct regulation of hospital prices to minimize the welfare loss from monopoly pricing.

In my third chapter, I look at the consequences of entry in NICU markets for a wide variety of outcomes using national data.

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# Chapter 1

# Inefficient Technology Investment: Competition, Mortality and Neonatal Intensive Care

## 1.1 Introduction

The setting I study is the market for neonatal intensive care for very low birth weight infants ($< 1500$ g.) in Texas. The very low birth weight (VLBW) population is of substantial interest due to its outsized contribution to overall infant mortality. These infants make up only 1.5% of all births, but represent more than 50% of all infant deaths in the US annually (see Tables (1.3) and (1.4)). Lowering the mortality rate for this population has the potential to result in substantial welfare improvements from modest reductions in the mortality rate. Very low birth weight infants are treated at birth in specialized neonatal intensive care units (NICUs). A large body of evidence on neonatal intensive care units suggests that mortality risk for VLBW infants is much lower when they are treated in higher-volume NICUs (e.g., [88]). The leading explanation for this effect is that there is learning by doing at the hospital level: hospital personnel learn to do better by doing more.

More broadly, healthcare services are an important setting characterized by increasing returns to scale in quality. Though the causal effects are difficult to identify, substantial evidence suggests that learning by doing in patient volume (and its converse, organizational forgetting) leads to economically meaningful differences in outcome quality across providers.

These effects require a different regulatory approach than that appropriate to a standard differentiated products oligopoly. In particular, entry of new NICUs may reduce total welfare by reducing average quality across all firms, while mergers may be welfare improving by improving quality.

Since the volume of very low birth weight patients is roughly fixed from year to year, entry into this market may be harmful: average patient volumes may be lowered across all hospitals, raising mortality risk. Conditional on a set of doctors and medical technologies, there do not appear to be any good substitutes for treating actual patients in learning how to produce better outcomes. Moreover, as I show in related work, high recent patient volume matters more than volume in the distant past. In this paper, I study the relationships among patient volume and quality of outcome (taking seriously the potential endogeneity of volume), model the incentives for firms to enter a market, and examine the consequences for aggregate welfare in Texas. The goal of this paper is to weigh the costs of entry against its benefits and to judge whether entry restrictions into the NICU market are warranted.

Hospitals in Texas have invested aggressively in NICUs since the cessation of entry restrictions in the mid 1980's (see Figures (1.8) and (1.10)). I show that these investments are not driven by capacity constraints at existing facilities using birth-certificate data on admissions to Texas NICUs. Rather, the primary motivation is business stealing from competitors. Investment is driven by the substantial increase in the total volume of patients admitted to the obstetrics ward which occurs after opening a NICU. Furthermore, this volume is far larger than what can be accounted for by the population plausibly in need of intensive care.

The problem of entry into markets characterized by economies of scale in the production of quality is a broad one. Such markets face a set of antitrust and regulatory concerns which are the mirror image of those in markets economies of scale in quality. In standard differentiated product settings without these scale economies, entry is generally beneficial and mergers are potentially harmful. Entry results in increased supply, lower prices and more convenient access to a product. Entry restrictions are welfare-reducing. Mergers increase market power and can raise prices, also reducing total welfare. On the other hand, entry in markets with economies of scale in quality may decrease average customer volume at all firms and lower average product quality, despite also lowering prices. Mergers in these markets can generate additional efficiencies beyond cost reductions by increasing consumer volumes and improving average quality, despite potentially increasing market power. The welfare gain from these effects can be larger than the loss due to higher pricing. A regulator failing to consider factors unique to markets with economies of scale in quality will get the sign of the welfare changes of entry or a merger wrong. Healthcare markets are an economically important setting characterized by increasing returns to quality in patient volume ([45] and [44]).

A large existing literature in health services research suggests that high patient volumes lead to better-quality outcomes. Though achieving credible identification is difficult, there is good reason to believe that higher-volume facilities produce better quality outcomes for patients as the result of learning by doing. In contrast to typical experience goods markets, in health care 'low quality' service can involve an appreciably higher risk of extremely serious outcomes, including mortality. Therefore, there is a significant tension between the benefits of price reductions vs. the costs of lower quality associated with market entry, and the costs of higher prices vs. the benefits of higher quality in mergers. While there are models of learning by doing and its effects on market concentration in the theoretical literature (including [6], [20], [23], and [34]) the papers do not consider the consequences for entry.

A credible study of the effects of regulatory interventions in this environment requires that I estimate a model with three components: (1.) a demand model for hospital services, (2.) a model of hospital investment incentives and (3.) a model of how patient volumes at the NICU affect patient mortality rates. To estimate the demand model, I use inpatient discharge data covering nearly all patients and hospitals in the state to estimate demand for hospitals as a function of hospital and patient characteristics. To understand firm incentives, I estimate a structural model of firm investment in this service, in which I recover firms' revenues and costs of treating patients in different severity groups, as well as the fixed costs of investing in neonatal intensive care. Estimates of these cost parameters are not available from other sources and are essential to the computation of counterfactuals. To estimate the relationship between patient volume and mortality I use birth-certificate level data for every patient admitted to a Texas NICU over eight years. Existing work in this literature typically does not control for the potential endogeneity of volume. I instrument for volume and show that the effects of volume on reducing the mortality rate are positive, causal and of meaningful magnitude.

I combine the three models to conduct two principal counterfactuals. In the first, I suppose that a social planner has the authority to designate which hospitals are permitted to open neonatal intensive care units. This corresponds to the kind of strict Certificate of Need regulation which already exists in many states. As a second counterfactual, I permit firms to invest freely, but allow the regulator to charge a fee for investment which increases in the number of firms servicing the market. This forces the firms to internalize some of the negative externality their entry imposes. In both cases, I find that these regulatory changes can result in less investment in each market, which concentrates volume and reduces mortality.

My counterfactuals show that hospitals do benefit from their investment: despite potentially treating a higher-cost patient population, the gains in revenue from general patient volume are large. Despite this, the overall mortality rate in a market increases as volumes decline everywhere. I show that centralizing the provision of these services would reduce the total mortality in this population in Texas annually by 20%. Entry restrictions are beneficial in this market. Similarly, a relaxed regulatory attitude towards hospital mergers can permit quality improvements via patient volume increases. I propose several ways the regulator could achieve this result, including consolidating existing facilities ([80]) or imposing minimum volume requirements.

A regulator examining markets characterized by all of these features needs to consider price effects, volume effects and the attendant effects on product quality and the fixed costs of investment jointly in computing welfare changes. If the regulator decides that the positive effects of high volume at a monopoly provider outweigh the negative effects of monopoly prices, entry restrictions are warranted. The regulator has an additional set of tools at his disposal to protect consumers from higher prices: direct regulation of prices. This ensures that the welfare loss due to monopoly pricing is not too large, but permits the monopolist to leverage the positive effects of volume. This will be welfare-improving compared to encouraging entry and competition.

Many states have an existing legal framework in place to implement entry restrictions in the form of "Certificate of Need" (CON) laws. These restrictions require that existing hospitals trying to enter a new service area, or entirely new hospitals trying to enter a market, prove that there is unmet demand for the services they would offer. Though these laws were not initially conceived with volume effects in mind, they provide an easy way for regulators to restrict entry. Additionally, there are informative examples outside of the US in which hospitals have have been closed to consolidate services among fewer providers. Better patient outcomes have been realized in these cases (e.g., [80] for perinatal care in Portugal, and [77] for stroke care in Manchester and London, England).

I can compute for each market what prices would have to be for hospitals to capture all of the potential welfare gained by increasing patient volumes and reducing mortality rates. I find that prices would have to be extraordinarily high for hospitals to appropriate all of this surplus. Finally, an additional potential disadvantage to entry restrictions comes in the form of increased travel times to receive services from more distantly-located patients. I can compute the implied per-mile cost that would be required to make the total welfare change neutral or negative in the service centralization case. I find implausibly large costs per mile are necessary. My conclusion is that the benefits of increased access through higher facility numbers are outweighed by the costs of higher mortality associated with reduced patient volumes.

## 1.2 Previous Literature

Studies of volume effects on the quality of outcomes are numerous in the public health literature. There are surveys in [76], [59], [69], and [83] among many others. The question has been extensively studied, starting as early as 100 years ago.[1] Results found in these

[1]See citation 1 in [76]

numerous studies suggest that hospital volume affects quality of care across procedures. Effect sizes vary, and achieving credible identification is difficult, but the relationship is positive: higher quantity leads to better outcomes. In light of this, there are programs aimed at centralizing some forms of critical care in the US and elsewhere. Empirical work on the effects of such regionalization programs also confirms that centralizing treatment can have a substantial positive effect on outcomes. [77] study the effect of regionalizing stroke care in London, which show substantial reductions in mortality from decreasing the number of hospitals offering stroke care in the greater London area. The prior literature on this effect in the context of neonatal intensive care is extensive: see [88], [28], [60], [65] or [80].

There is a connection between the model proposed here and the "medical arms race" (MAR) literature (see [37]). That literature proposed that hospitals would over-invest in technology in order to attract physicians and their patients. This is a form of competition on quality, rather than price, as hospitals vertically differentiate themselves by offering the most advanced facilities to the physicians in their market. (The "arms race" describes the idea that consumers do not benefit from this form of competition.) Costs to insurers and consumers increase to cover the costs of hospitals' over-investing. Empirical evidence on this hypothesis is mixed (see [38], [37], [47]). My project is related to that literature in that I attempt to assess how the profitability per-patient changes with the number of hospitals in the market, but I add and measure the possibility of welfare loss through lower-quality service.

An important feature of this market is that improvements in patient mortality are driven by facility-level learning. This is not a one-way process: when patients are not seen, accumulated knowledge depreciates. Learning by doing is the subject of a large literature, including studies which estimate rates of forgetting. Implied monthly rates of forgetting are generally quite high. Forgetting is on the order of 3% - 5%: see [17], [110], [107] and [108]. Learning by doing models and related work are surveyed in [109]. Work in this literature in the context of health care includes [98], [45], [44]. [64] estimate a surgeon-specific human capital depreciation rate in coronary artery bypass graft procedures in Pennsylvania and find that each *day* away from surgeries increases patient mortality risk by 0.07 percentage points.

Other related work includes studies of hospital competition on quality ([68], [46], [31], [57]), the effects of investment in neonatal intensive care units on outcomes ([42, 88], [13]), studies of the effects of the volume of medical procedures on the quality of outcomes ([63], [54], [92]) and structural models of firm investment, including [29] and [95]. There are also several dynamic structural models of hospital behavior, including [56], [97] and [**?**].

My paper builds on their earlier work along several dimensions. Like [97], but unlike [56], the investment process I model corresponds to something directly observable in the data. In contrast to [97], I observe all of the patients in the Texas market, so I can compute demand directly from that data. More importantly, there is an explicit welfare dimension to my paper via the tension between positive volume effects and the increased convenience of access arising from decentralization. Finally, there is a connection between this paper and an earlier theoretical literature on entry restrictions in homogeneous goods markets [73], in which free entry resulted in excessive entry, studied empirically in radio markets by [19] and [18].

## 1.3 Industry Overview

### 1.3.1 NICUs

Neonatal intensive care has its origins in the birth of the infant incubator in France in the late 19th century ([11]). The technology was brought to the United States in the early 20th century and spread slowly due to skepticism within the medical profession. Interestingly, the very first specialized facilities to care for these infants in the United States were not hospitals but amusement park attractions ([11], [21], [84], [90]). Prior to the existence of NICU's, hospitals left the very premature to the care of their parents, since there was nothing that could be done to improve the outcomes for them medically ([11]). Most would die soon after leaving the hospital.

In the 1960's, formal perinatal regionalization programs began to coordinate care and patient transfers among hospitals with and without intensive care units for premature infants ([7]). One of the most transformative technological developments of the 1990's for very low birth weight infants was the introduction of surfactants, which aid breathing in underdeveloped lungs. Substantial improvements in outcomes for this set of infants were achieved between the 1950's and 1990's, though progress may have stalled ([66]). A substantial fraction of the overall improvement in infant mortality in the United States over the past half century can be credited to changes in the outcome for the very low birth weight population.

Most infants are admitted to the NICU due to prematurity (<37 weeks). In 2012, 9.8% (roughly 385,000) of all infants born in the United States were premature ([115]). 8% were low or very-low birth weight ([115]) - that rate is about 1% higher in Texas. Neonatal intensive care units are differentiated by levels (numbered 1-3) depending on the quality of service provided. This classification scheme is used throughout the United States.[2] The lowest level designation (Level I) covers general labor and delivery services which are available in any hospital that handles labor and delivery. Should an infant needing intensive care be born in a hospital with a Level I facility, that facility must have the ability to stabilize and transfer the patient to a higher level NICU ([4]). Level II facilities (neonatal *intermediate* care) generally provide more advanced care (excluding surgery) for sick infants, except those weighing less than 1500 grams (i.e., those who are VLBW) and do not provide long-term mechanical ventilation. Such a facility should be able to care for infants born at more than 32 weeks gestation. Level III facilities (neonatal *intensive* care) provide mechanical ventilation of unlimited duration, surgery, and the full range of specialized services available to neonates. Importantly, the definitions of Levels I, II and III have remained constant in the Texas Annual Survey of Hospitals between 1990 and 2012, the period I study.

### 1.3.2 NICU Investment

Hospitals in Texas have invested aggressively in building new NICU's since the early 1990's. Figures (1.8) and (1.10) show the total number of hospitals in the state, and each bar has been split into three categories, tracking the number of facilities at Levels I, II and III over time. Most of the new facilities entered counties which had at least one existing NICU (see Figures (1.13) and (1.14)), and thus are not expanding access to geographically unserved areas. Specializing to hospitals in populous counties (here defined to be those with more than 250,000 inhabitants), Figure (1.10) shows that the number of hospitals offering

[2] Starting in 2018, Texas will introduce a classification scheme including a Level 4 facility, but that does not affect the time period I study, which ends in 2012.

only Level I services drops from about half in 1990 to perhaps one quarter by 2012, while more than half upgrade to Level III services by the end of the time period. Competitive pressure among hospitals in urban areas drives the investment. These effects are not driven by capacity constraints at existing NICUs, as I show in the next paragraph.

Using birth certificate data containing information about the hospital of birth, I can compute several measures of utilized capacity in NICU's. I do not observe the date of admission and discharge, so I cannot compute durations of stay for any patient. I compute several indirect measures of capacity utilization instead. First, I compare the total number of admissions to the NICU for the whole month to the number of beds in the NICU, which I take from the hospital survey. The results are in Table (1.5) in the second column. Only a third of hospital-month observations see more patients admitted to the NICU *for the whole month* than there are beds in the facility. Second, I use the average duration of stay in a NICU (13.2 days) to compute the mean and median free days per bed, assuming that each patient admitted in the month has a stay of average duration. I find that there are on average 16-18 free days per bed per month. The median number of free days per bed under the same assumption is 19-20. These measures suggest that it is very unlikely that existing facilities are near their capacity constraints.

One driver of investment has been a shift in the underlying demand for NICU services. This is due to an increase in the number of women over age 30 giving birth in the state. In Figure (1.2), the rate of admission of infants to the NICU is plotted as a function of the age of the mother. The rate doubles from 6% to 12% as age increases from 30 to 49.[3] In Figure

[3]The rate for women older than 50 is 35%, which is much higher than the rates plotted, but there are generally fewer than 100 such births every year in Texas.

(1.3) the fraction of all births occuring to women above age 30 is plotted. This number increases from just over 26% in 1990 to nearly 34% in 2010, the last available year for this data set. This understates the total increase, considering the magnitude of the population growth in the state between 1990 and 2012. There were 316,000 births in Texas in 1990. In 2010 there were 385,000. 26% of all births in 1990 is around 82,000 births, while 34% of all births in 2010 is 130,900. While demand conditions were changing due to an increase in the number of mothers having babies above age 30, the growth of the population reinforced that trend.

One of the most compelling reasons for hospitals to invest in new NICU facilities, however, is that a hospital without a high level NICU may lose business to one which does have one. Most women will not know in advance of the onset of labor whether they will need NICU services. Because the consequences of not having high-level NICU services available if they are necessary can be severe, a precautionary motive may cause mothers to plan their labor and delivery for a hospital with those services. This is visible in data from Texas in figure (1.7). The mean number of total births at a hospital in the two years *prior* to the construction of an NICU grows only slightly, but by the end of the second year after the construction of a NICU, total birth numbers have increased by about one third. Given that the number of infants who need Level III services is about 13% of all births, it is unlikely that this increase is driven solely by the provision of high-level NICU services. A large number of women will choose to use the hospital but will not end up needing those services.

Evidence from Medicaid reimbursement rates in Texas suggests that while uncomplicated deliveries might yield a $1200 reimbursement to the hospital, providing the most high-level services to very sick neonates can be reimbursed at rates up to $100,000 ([105],

[106]). While NICU services are more expensive for providers, observed investment suggests again that hospitals are unlikely to lose substantial sums by opening NICU's. In fact, the reverse is likely true. Reimbursement amounts by private insurance companies are unlikely to be lower than those for Medicaid, so the above figures are a lower bound on the true reimbursements. Investment in NICU services is driven by the opportunity to provide lucrative, highly-reimbursed services to a subset of the patient population, but also by the fact that entirely new patients are drawn to the hospital.

### 1.3.3 Certificate of Need Regulation

Certificate of Need regulations are relevant to this paper to the extent that they give states a way to prevent both entry into new service markets by existing hospitals and entry of entirely new hospitals. Certificate of Need programs were originally motivated by concerns that hospitals would over-invest to attract doctors with advanced facilities, become highly indebted, and not have enough patient revenue to cover their costs ([96]). States were eventually compelled to adopt this regulation ([79]). Certificate of Need laws were in force in 49 states by 1979 ([96]) then began to be repealed in the mid to late 1980's, including in Texas. A majority of states currently retain some kind of CON regulation ([78] and Figure (1.4)). CON permission to offer certain services provides something of value to hospitals, most likely via market power, because the certificates themselves are valuable assets which can be sold during bankruptcy proceedings as has happened at least twice in Florida ([101], and [114]). While CON regulations were not implemented with volume effects in mind, they provide a simple way for states to restrict investment with an existing legal infrastructure.

| City | Total NICU Admits at Birth | Total Level 3 Beds | Bed-Days Available | Bed Days Available Per Admit | Admits to Reach 90% Capacity |
|---|---|---|---|---|---|
| San Antonio | 2271 | 141 | 51465 | 22.6 | 3508 |
| Houston | 5528 | 371 | 135415 | 24.5 | 9232 |
| Fort Worth | 2474 | 152 | 55480 | 22.5 | 3782 |
| Dallas | 3138 | 365 | 133225 | 42.5 | 9083 |
| Austin | 1451 | 131 | 47815 | 32.4 | 3260 |
| All Large Counties, > 250,000 | 21159 | 1621 | 591665 | 27.9 | 40,340 |

Table 1.1: NICU Capacity in Large Texas Counties

| County | | Total Births | Total LBW | Total VLBW | % LBW | % VLBW |
|---|---|---|---|---|---|---|
| Travis | Mean | 21055 | 1745 | 349 | 8.3 | 1.6 |
| | St. Dev. | 1000 | 35.6 | 21 | 0.29 | 0.13 |
| Bexar | Mean | 30274 | 2959 | 525 | 9.9 | 1.7 |
| | St. Dev. | 749.5 | 92 | 32.5 | 0.18 | 0.08 |
| Harris | Mean | 74916 | 6857 | 1324 | 9.15 | 1.8 |
| | St. Dev. | 2728 | 333.6 | 68 | 0.15 | 0.06 |
| Texas | Mean | 404,259 | 34,264 | 5915 | 8.4 | 1.45 |
| | St. Dev. | 9559 | 998 | 200 | 0.05 | 0.05 |

Table 1.2: Mean Births, Low Birth Weight Births, Very Low Birth Weight Births in Four Large Texas Counties, 2005 - 2010

| | Births | LBW | VLBW | % LBW | % VLBW |
|---|---|---|---|---|---|
| Average | 3,903,012 | 286,149 | 53,060 | 7.3 | 1.4 |
| St. Dev. | 132,283 | 22,695 | 3,385 | 0.32 | 0.03 |

Table 1.3: Total US Birth Category Averages, 1995 - 2010

| | Infant Deaths | LBW | VLBW | % LBW | % VLBW |
|---|---|---|---|---|---|
| Average | 27,439 | 18,317 | 14,400 | 67 | 52 |
| St. Dev | 1,054 | 841 | 725 | 2.1 | 1.9 |

Table 1.4: Average US Infant Deaths Within One Year of Birth by Weight Category, 1995 - 2010

| Year | Frac. Months w/ Admits > Beds | Mean (SD) Free Days Per Bed, w/ Stays Avg. Duration | Med. | Mean (SD) Free Days Per Bed, w/ Stays 2 × Avg. Duration | Med. |
|---|---|---|---|---|---|
| 2005 | 37% | 16 (12) | 19 | 3 (25) | 9 |
| 2006 | 39% | 16 (12) | 19 | 2 (25) | 9 |
| 2007 | 40% | 16 (12) | 19 | 3 (25) | 8 |
| 2008 | 37% | 17 (13) | 20 | 5 (26) | 10 |
| 2009 | 36% | 16 (13) | 20 | 4 (27) | 10 |
| 2010 | 36% | 17 (13) | 20 | 5 (26) | 10 |
| 2011 | 32% | 18 (11) | 20 | 7 (23) | 11 |
| 2012 | 37% | 17 (11) | 20 | 5 (22) | 9 |

Table 1.5: Direct Measurements of NICU Capacity Utilization, Incl. Patients Transferred In

## 1.4 Data

I use four main sources of data in this paper. I use the Texas Department of State Health Statistics (DSHS) Annual Hospital Survey, which tracks hospital investment, as well as market entry and exit ([104]). I use DSHS' Inpatient Discharge Public-Use Data File, which contains data on nearly every inpatient admission in the state, including the complete set of births at all but a very small number of hospitals. To estimate the volume-outcome relationship, I have birth-certificate level data from Texas DSHS which contains the name of the birth hospital. To compute some summary measures of NICU admission, I use the National Center for Health Statistics Linked Cohort Birth/Death Files.

### 1.4.1 Data on Hospitals

The Texas Department of State Health Statistics Annual Survey of Hospitals provides information on hospital services, several measures of utilization and some financial variables annually between 1990 and 2012. The survey is administered jointly with the better known Annual Survey of the American Hospital Association. I have linked the surveys across years, so I can reconstruct a complete picture of all the services offered at the facility level for the entire study period. I observe all possible transitions among levels in the data, including upgrades and downgrades.

All hospitals in the state, except for a small collection of facilities in rural counties and a few specialty hospitals primarily serving children, must complete the report. The children's hospitals are an important missing set of data. The data also include specialty hospitals which are not relevant for my purposes. A heart hospital, for example, is very unlikely to decide to start offering labor and delivery services or neonatal intensive care. I

| Description | Count | Fraction | Mean | Variance |
|---|---|---|---|---|
| Total Hospitals, 1990 | 315 | - | - | - |
| Total Hospitals, 2012 | 280 | - | - | - |
| Hospitals For-Profit | - | 0.45 | - | - |
| Level III, 1990 | 54 | .17 | - | - |
| Level III, 2012 | 101 | .37 | - | - |
| Level II, 1990 | 31 | 0.09 | - | - |
| Level II, 2012 | 28 | 0.10 | - | - |
| Level III Capacity (Beds) | - | - | 21 | 17.69 |
| Level II Capacity (Beds) | - | - | 7 | 4.6 |
| Pediatric Intensive Care | - | 0.09 | - | - |
| Obstetrics Level (1-3) | - | - | 1.6 | 0.69 |
| Total Deliveries > 20 Wks. | - | - | 1183 | 1722 |
| Total Beds | - | - | 168 | 182 |
| Full-time Registered Nurses | | | 190 | 270 |
| Unique Counties Represented | 155 | 0.61 | - | - |
| Fraction in Metropolitan Areas | - | 0.62 | - | - |

Table 1.6: Summary Statistics for Hospitals

exclude hospitals unless the number of births it sees in some year in the data exceeds 10. This enables me to capture some rural hospitals which do see births in very low numbers, and could upgrade the services they provide. Summary statistics about the hospitals in the sample are in Table (1.6).

The map in Figure (1.5) shows the coverage by county. Most hospitals in the state are located in cities or suburban areas. Counties with no number had no hospitals in any year of the DSHS survey period.

| Transitions | Count |
|---|---|
| **Level II Total** | 88 |
| Level I to Level II | 66 |
| Level III to Level II | 22 |
| **Level III Total** | 111 |
| Level II to Level III | 49 |
| Level I to Level III | 62 |

Table 1.7: State Transitions Observed

### 1.4.2 Data on Inpatient Admissions

The main source of inpatient data is the Texas Hospital Inpatient Discharge Public Use Data File, published quarterly since 1999. The Public Use Data File contains discharge-level records of hospital admissions, including a wide range of diagnosis and procedure codes for nearly all inpatient admissions in the state, including nearly all of the births recorded in the state each year. The 2005 file records about 381,000 births, while there were roughly 385,000 births in the state in that year ([103]). Patient DRG (diagnosis-related group) codes, which for the pregnant women and infants are never missing, enable me to identify the fraction of infants born at low birth weight in the inpatient data. [72] report that 8.3% of all babies born in Texas in 2005 (roughly 31,000) were low birth weight. The inpatient data do include hospital charges, but actual transacted prices, whether from insurers to hospitals or patients to hospitals, are not available in my data. I will discuss this limitation at greater length later.

For each patient, I observe the five digit zip code of residence, provided more than 10 patients from the zip code are in the inpatient discharge records. This requirement is easily met nearly everywhere in the state. The map in Figure (1.6) illustrates the coverage of the

| Description | N | Fraction | Mean | Variance |
|---|---|---|---|---|
| Infants: Males | 194,605 | - | - | |
| Length of Stay | - | - | 3.59 | 8.62 |
| Unique Zip Codes Represented | 1734 | - | - | |
| Patients Per Zip | - | - | 1306 | 984 |
| Unique Counties | 244 | 0.96 | - | - |
| Hispanic Origin | - | 0.45 | - | - |
| White | - | 54.5 | - | - |
| African-American | - | 10.5 | - | - |
| Medicaid Patients | 184,457 | 0.49 | - | - |
| Commercial Insurance | 150,792 | 0.39 | - | - |
| Mean Total Charges | | | 8558 | 46214 |
| Risk of Mortality (1-4) | - | - | 1.04 | .29 |
| Unique Hospitals | 230 | - | - | - |

Table 1.8: Patient Summary: 2005 Data

inpatient data: the shapes are US Census Zip Code Tabulation Areas. The blank areas are parts of the state with extremely low population. Using all of the years of available inpatient admissions data, I can compute the mean and variance of the number of patients in each DRG category at the zip code level. There are seven pregnancy-related DRGs (numbered 385 - 391 prior to 2007) and the number of patients in each category varies by year by zip code. I use these zip-code level means and variances to draw the size of the patient population in my simulations.

I do not observe any patients' insurance provider, so I cannot make any inferences about which hospitals are in or out of network for any patient. I do, however, differentiate between patients with Medicaid and patients with private insurance. Hospital choice sets are constructed in the following way: the choice set is taken to be the closest 10 hospitals within 50 miles, plus an outside option. I exclude patients for which the measured distance from the chosen hospital to the zip code is greater than 70 miles. This represents the 99th percentile of the data on measured distances from hospitals to zip code centers for all patients. For example, in the full sample of patients from 2005, there are 2,800,000 inpatient discharge records (including all non-labor and delivery related admissions). Limiting to those inpatient discharges which are associated with labor and delivery episodes, I find that 48% of all discharges covered by Medicaid and 41% are covered by private insurance. Since these are the vast majority of the sample, the exclusion of those covered by other types of insurance is justified.

### 1.4.3 Data on Volume Effects

The birth certificate data which I use also comes from the Texas Department of State Health Services, covering a period from 2005-2012, and includes infant who was either admitted to a NICU, who died within 28 days after birth, or who was low birth weight ($<$ 2500 grams, which includes very low birth weight). For these patients, I have information about the hospital in which the birth occurred, a variety of covariates concerning the birth itself (e.g., C-section or vaginal, etc.), plus health status information for the mother and the infant. This data also includes the name of the destination facility for any transfer of the mother or the infant. This information can be matched with information from the Annual Hospital Survey about facilities available at the hospital for 90% of all records in the data. Each record can be matched to the zip code of the mother's residence, then distance to the chosen facility is computed.

### 1.4.4 National Birth Certificate Data

Finally, in a few places I make use of the National Center for Health Statistics' Linked Birth/Infant Death Cohort Data. This dataset combines information from birth certificates (without the hospital ID) with some limited discharge information and represents the complete set of infants issued birth certificates in every state each year. Because it excludes the identity of the hospital, I cannot make direct inferences about the volume of patients in a particular hospital using this source. It contains a broad spectrum of covariates recording information about the mother, father, place and manner of delivery, prenatal care, health conditions related to the infant, and other relevant data. NICU admissions are also recorded. For infants and neonates who died within one year, there is a supplementary file which records information relating to the cause of death. I use this information to compute the probability of admission to an NICU as a function of maternal age, and also to measure the changes in average maternal age over time. This data enables me to count the number of patients admitted to the NICU within counties, count the total number of births, and assess the rates of various complications in the entire state over time.

## 1.5 Model

The model has three components: a demand model in which patients choose a hospital for their birth episodes, a model of the volume-outcome relationship and a structural hospital investment model. The first model is static, the second two are dynamic. I combine all three to compute my counterfactuals and welfare measures.

Demand for hospital services is the sum of all of the individual demands for the service at each DRG in every given period. For the purposes of the simulation, the parameters of the individual choice model are recovered separately for Medicaid and privately insured patients since these populations may differ along a number of important dimensions. Each period of the simulation, I draw from zip-code level means and variances of the number of patients in each of seven pregnancy-related DRGs to represent the patient population in that year in that zip code, capturing the fact that there is substantial heterogeneity in the mean and variance of the number of patients giving birth each year at the zip code level. Each patient drawn in each DRG category chooses her preferred hospital among the 10 in her choice set, or chooses the outside option.

I merge data on hospitals from the Annual Survey of Hospitals into the inpatient data. This enables me to determine whether a given hospital has neonatal intensive or intermediate care. I can also determine which other hospitals in the patient's choice set offered these services, as well as distances, number of beds, whether the hospital is closest, or any other relevant feature.

### 1.5.1 Patient Choice Model

I suppose that the patient and her doctor makes a utility-maximizing choice of hospital as a function of their distance from the facility, the facility's level of service (intensive or intermediate), whether it is the closest facility to the patient and an interaction between the distance to the facility and the number of beds, plus an error. Because of the important role of the doctor in determining the choice, this is best thought of as a joint decision between the doctor and the patient (this is a common assumption in this literature, e.g., [62]). The patient's utility specification is linear in these features of the hospital. Utility for patient $i$

at hospital $j$ has the form

$$\begin{aligned} U_{i,j} &= \bar{U}_{i,j}(H_j, X_i, \lambda_{i,j}) + \epsilon_{i,j} \\ &= \alpha H_j + \beta X_i + \gamma \lambda_{i,j} + H_j' \Omega X_i + \epsilon_{i,j} \end{aligned} \tag{1.1}$$

where $H_j$ is a vector of hospital characteristics, $X_i$ a vector of patient characteristics, $\lambda_{i,j}$ the distance from $i$ to $j$ and $\epsilon_{i,j}$ is a Type-I Extreme Value error. Patient characteristics here are the patient's DRG, hospital characteristics are the levels of NICU services provided (Level II or Level III). An interaction between the number of beds and the distance to the patient's zip code is also included. The results of the model indicate that patients are sensitive to distance, and have strong preferences for higher level NICU facilities.

Medicaid and privately insured women in the same zip code are assumed to face the same choice sets for hospitals. This is a necessary simplification, given that insurance networks are unobserved, but this problem is common in this literature, for example in [102]. Most Texas Medicaid patients are on Medicaid managed care, which means that they will generally face restricted networks too, but these networks are also unobserved. Therefore, I assume that all patients can choose among all of their closest available hospitals. In practice, more than 80% of women in the data choose one of the 10 closest hospitals to their zip code of residence. I have estimated another version of the model which allows patients to choose among their 50 closest hospitals. Those results are in Table (1.10). Relative to the model with fewer choices, the coefficients on measures of distance stay the same, while those for the intensive and intermediate facilities increase substantially. For computational reasons, I use the model with fewer choices in my simulations: increasing the number of choices for each patient slows estimation down dramatically.

| Variables | Mean | Variance |
|---|---|---|
| Distance (miles) | 8 | 6.5 |
| Intensive | 0.52 | .49 |
| Intermediate | 0.14 | 0.34 |
| Closest | 0.185 | - |
| Dist × Beds | | |

Table 1.9: Patient Choice Model Parameters: 10 Closest Hospitals

While some cost information is included in the inpatient data for both privately insured and Medicaid patients, the prices submitted are on the basis of full charges. They do not represent either how much the insurance company paid the hospital (generally a steep discount over the full charges) or how much the patient's copay was. It is impossible to include any measure of the price the patient actually paid to receive the service. This, too, is a frequent data limitation in this literature, e.g., [62].

It is an important identifying assumption in the model that women do not simply choose the closest hospital, ignoring other hospital characteristics, such as facility levels. Fortunately, this is not what we observe. The average distance to the closest hospital in the choice set is 5 miles. The average distance to the chosen hospital is 11 miles. Excluding those who traveled 75 miles or more, more than 80% of all women choose one of the 10 closest hospitals, but only 18% choose the closest. The fraction of women choosing the N-th closest hospital is plotted in Figure (1.12). Hospitals further away than the 10 closest are combined into one category at the right.

The results of this model when estimated jointly and separately for Medicaid and privately insured patients (without any DRG-specific terms) appear in table (1.11). The coefficients all have the expected signs: patients prefer closer facilities and value higher levels

| Coeff. | Combined | Priv. Ins. | Medicaid |
|---|---|---|---|
| Dist. | -0.17 | -0.20 | -0.16 |
| | (0.0009) | (0.002) | (0.001) |
| Dist. Sq. | 0.0004 | 0.00056 | 0.0004 |
| | (4.5e-06) | (7.5e-06) | (7.0e-06) |
| Intensive | 6.82 | 7.90 | 6.21 |
| | (0.17) | (0.42) | (0.20) |
| Intermediate | 5.34 | 6.98 | 4.58 |
| | (0.115) | (0.185) | (0.186) |
| Distance×Beds | 0.001 | 0.002 | 0.002 |
| | (0.0001) | (0.0002) | (0.0002) |
| Closest? | 0.343 | 0.209 | 0.441 |
| | (0.01) | (0.019) | (0.017) |
| N | 86,279 | 35,819 | 42,057 |
| Hospital FEs | Y | Y | Y |

Table 1.10: Patient Choice Model Parameters: 50 Closest Hospitals

of service. The coefficients are very similar across the patient categories, though Medicaid patients show greater sensitivity to distance, perhaps reflecting an increased cost of traveling. The results in this table are similar to those in [55], though those authors use travel times instead of distance in miles. All of these features of the data are observed, so this model is estimated by maximum likelihood.

### 1.5.2 Volume-Outcome Relationship

Birth certificate data covering 2005 to 2012 enables me to estimate the relationship between patient volume and the quality of patient outcomes in Texas NICU's. This is described at greater length in my paper [16]. I use birth-certificate data to compute a complete count of all patients admitted to the NICU at each hospital in the state. I have

| Coeff. | Combined | Priv. Ins. | Medicaid |
|---|---|---|---|
| Dist. | -0.179 | -0.19 | -0.189 |
| | (0.003) | (0.005) | (0.005) |
| Dist. Sq. | 0.002 | 0.003 | 0.002 |
| | (0.00007) | (0.0001) | (0.0001) |
| Intensive | 2.635 | 2.485 | 2.689 |
| | (0.113) | (0.136) | (0.227) |
| Intermediate | 0.425 | 0.404 | 0.447 |
| | (0.091) | (0.14) | (0.153) |
| Distance×Beds | -0.001 | -0.001[4] | -0.001 |
| | (0.0005) | (0.0008) | (0.0008) |
| Closest? | 0.332 | 0.263 | 0.331 |
| | (0.014) | (0.024) | (0.02) |
| N | 86,279 | 35,819 | 42,057 |
| Hospital FEs | Y | Y | Y |

Table 1.11: Patient Choice Model Parameters

information about the month and year of birth, so I can compute how many patients were at each NICU during each month. This enables me to compute various capacity measures, but it also permits me to investigate how the number of patients admitted to the NICU affects the outcomes for those patients admitted subsequently. Summary statistics about this patient population for each year in the data are included in Table (1.13).

I present the results of several models measuring the effects of patient volume on quality in [16]. The results are consistent with earlier estimates from [88] and others, who also find a negative effect of higher patient volume on mortality (though [88] observe patient volumes by calendar year only). I report two sets of estimates here. First, I estimate a probit model for mortality, controlling for individual health states $X_i$, gestational age $\psi_w$ (which is closely correlated with birth weight), year fixed effects $\phi_t$, patient insurance status $\pi_s$, and including a lagged hospital-specific volume term $v_h$ which records NICU admissions for the previous quarter. I also include an indicator for whether the patient is very low birth weight. The coefficient of interest is the $\gamma$ on the lagged patient volume.

$$\begin{aligned} y^*_{i,h,t} &= \alpha + \beta X_i + \gamma v_h + \sum_w \psi_w + \sum_t \phi_t + \sum_s \pi_s + \delta 1_{wt<1500g.} + \epsilon_i && (1.2) \\ y_i &= 1_{\{y^*_i>0\}} && (1.3) \end{aligned}$$

Without correcting for endogeneity in patient volume, I find that the coefficient $\gamma$ is negative is negative and precisely estimated: higher patient volumes lead to lower mortality probabilities later. The value is reported in Table (1.12). Admission to a particular hospital is not randomly assigned, but is endogenously determined by the patient and doctor jointly. In particular, choices are likely to be a function of unobserved hospital quality.

The most plausible selective referral pattern biases estimation against finding any negative effect of volume on the probability of mortality. If hospitals differ in unobserved quality and patients in an unobserved mortality risk type, sicker patients at higher risk of mortality are likely to be referred to higher quality hospitals. This raises the average mortality risk of the population at higher-quality hospitals (which also have a higher volume of patients). At the same time, it lowers average mortality risk in the population at hospitals which are referring patients out (which now have lower patient volumes). Provided there are not transfers of lower-mortality-risk patients from high quality facilities to lower-quality facilities, which seems unlikely, the naive estimation of volume effects on quality is likely to underestimate the role of volume in producing quality outcomes. An instrument for patient volume which I will outline in subsequent paragraphs permits identifying the underlying causal effects.

I estimate the same model again, instrumenting for patient volume using predicted patient volume a strategy similar to one used by [44], and [54]. [54] estimate a model of patient choice as a function of patient, hospital and patient-hospital (e.g., distance) characteristics. They aggregate the probabilities of choice across patients to create a measure of predicted patient flows. These patient counts then are used to instrument for hospital volume: they should be correlated with actual hospital volume, but will not otherwise affect patient mortality.

Similarly, [44] count the number of patients at a set of fixed radii, the number of hospitals, and a set of year dummies to instrument for volume. These capture the fact that a hospital's volume depends on both the number of patients and the number of other hospitals in the market. [44] do not estimate a patient choice model on the basis of hospital features, but this makes sense in their setting since hospitals providing the procedure they study (coronary artery bypass grafts) are not distinguished by level.

My procedure is similar to that in [54]: I compute the patient choice model as a function of exogenous characteristics of patients and the hospital, then sum the resulting choice probabilities. This gives a measure of volume which is not correlated with unobserved facility quality - by construction since the choice model was estimated with only observable characteristics. I use this predicted measure as an instrument for actual hospital volume.

I give all patients the choice of any of the 50 hospitals closest to their zip code of residence.[5] The instrument captures the fraction of variation in volume that is driven by observable characteristics of the facilities, not by unobservable quality. The main identifying assumptions are that the predicted volume $\hat{v}_h$ is correlated with actual hospital volume $v_h$, and that $\hat{v}_h$ does not enter into the mortality function (2.1) and is orthogonal to the error in (2.1).

I use this to instrument for quality in the following probit model:

$$
\begin{aligned}
y^*_{i,h,t} &= \alpha + \beta X_i + \gamma v_h + \sum_w \psi_w + \sum_t \phi_t + \sum_s \pi_s + \delta 1_{wt<1500g.} + \epsilon_i && (1.4)\\
v_h &= \alpha' + \beta' X_i + \sum_w \psi'_w + \sum_t \phi'_t + \sum_s \pi'_s + \gamma' \hat{v}_h + \epsilon'_i && (1.5)\\
y_i &= 1_{y^*_i>0} && (1.6)
\end{aligned}
$$

Volume $v_h$ is endogenous. The exogeneity of volume is rejected across all of the IV specifications I use. I report the quarterly lagged volume coefficients in Table (1.12). I have estimated specifications with prior year volume, prior quarter, four prior quarters, prior month and prior 12 months and I find similar outcomes across specifications.

As expected the coefficient on lagged volume is negative and significant. The partial effects of volume at the mean of other covariates are presented in Figure (2.1). The sign of the effect is compatible with a plausible story of endogenous patient referral across facilities. In the simulations I conduct later, I use the mortality risks implied by the partial effects in Figure (2.1). Another feature to emphasize about these results is that the effects themselves

[5] In the average quarter, the 50th-closest hospital is chosen by about 40 of 85,000 patients. On average, fewer than 50 patients per quarter choose any hospital 45th-closest or further. The 50th-closest hospital is on average 60 miles away from the center of the patient's zip code, with a standard deviation of 36 miles.

are of significant magnitude. The effect of moving a patient from the lowest volume facility to the highest volume one cuts the patient's mortality risk by two thirds.

| | Probit | IV Probit |
|---|---|---|
| Neonatal Death | | |
| Prior Quarter NICU Admits | -0.000567*** | -0.000209* |
| | (0.0000728) | (0.0000985) |
| Observations | 185817 | 185817 |
| Health States | Y | Y |
| Gestational Age | Y | Y |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.12: Volume Outcome Probits

Several alternative specifications are estimated in [16]. The results I present here are for the lagged prior quarter volume, but the results are substantially similar when using prior month or prior year. In [16] I also estimate several models to demonstrate that the more recent the volume is, the more important an effect it has in terms of reducing the mortality rate. The results suggest that improvements in mortality rates due to learning at the facility are quickly forgotten. For more details, see [16].

### 1.5.3 Hospital Investment

My model of hospital behavior fits into the framework of [39] and [36]. Time is discrete, and the horizon is infinite. Each firm is a single hospital. Each firm's state is a vector

$$n_i = (l_i, h_1^{0-5}, h_2^{0-5}, h_3^{0-5}, h_1^{5-15}, h_2^{5-15}, h_3^{5-15}, h_1^{15-25}, h_2^{15-25}, h_3^{15-25})$$

| Characteristic | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|---|---|---|
| Patients | 43082 | 45338 | 46039 | 47132 | 48039 | 46647 | 45660 | 46400 |
| Mortality Rate (/1000) | 33.5 | 32.4 | 31.0 | 30.2 | 28.5 | 29.7 | 28.5 | 28.4 |
| Percent Born in Hospital | 99.7 | 99.6 | 99.6 | 99.6 | 99.6 | 99.5 | 99.6 | 99.6 |
| Unique Hospitals | 273 | 275 | 267 | 271 | 276 | 262 | 264 | 261 |
| Fraction Male | 0.508 | 0.506 | 0.505 | 0.510 | 0.509 | 0.508 | 0.510 | 0.510 |
| Estimated Weeks Gestation | 35.1 | 35.1 | 35.1 | 35.2 | 35.2 | 35.2 | 35.2 | 35.2 |
| (S.D.) | (4.5) | (4.4) | (4.5) | (4.4) | (4.2) | (4.2) | (4.2) | (4.2) |
| Birth Weight (grams) | 2312 | 2313 | 2309 | 2328 | 2343 | 2369 | 2372 | 2390 |
| (S.D.) | (779) | (783) | (776) | (773) | (781) | (788) | (795) | (820) |
| Transferred (%) | 7.5 | 6.8 | 6.9 | 6.2 | 6.2 | 6.0 | 6.4 | 5.2 |
| Distances Traveled | | | | | | | | |
| Average Distance Traveled | 12.8 | 12.5 | 12.6 | 12.6 | 12.5 | 12.6 | 12.7 | 12.7 |
| (S.D.) | (14.6) | (14.1) | (14.1) | (14.3) | (13.8) | (14.1) | (14.5) | (14.4) |
| Distance 5th Percentile | 1.6 | 1.6 | 1.6 | 1.6 | 1.7 | 1.7 | 1.6 | 1.6 |
| Distance 95th Percentile | 38.1 | 36.8 | 36.7 | 37.6 | 37.0 | 36.8 | 37.7 | 37.7 |
| Insurance Status | | | | | | | | |
| Medicaid | 43.6 | 43.7 | 43.8 | 46.8 | 49.2 | 50.2 | 50.4 | 48.8 |
| Private | 37.6 | 35.9 | 36.6 | 36.8 | 35.7 | 35.4 | 35.8 | 36.0 |
| Self-pay | 13.9 | 16.9 | 14.4 | 10.7 | 9.0 | 8.3 | 7.3 | 7.5 |
| Other/Unknown | 4.8 | 3.51 | 5.2 | 5.75 | 6.1 | 6.2 | 6.5 | 7.7 |

Table 1.13: Birth Certificate Sample Characteristics

of the level of its competitors at distances 0-5 miles, 5-15 miles and 15-25 miles and its own level $l_i$. This reflects the fact that a hospital will view the same investment by different firms in its market as a better or worse substitute for the service which it provides. Hospitals which are better substitutes are more important to the hospital's strategic behavior. Naturally, its investment decisions also depend on what level of facility already exists at the hospital. The firm also observes a private shock $\epsilon_i^t$ each period. The $\epsilon_i^t$'s are independently and identically distributed. Private information shocks are needed to ensure the existence of pure-strategy equilibria, as in [36]. The firm's state is characterized by the pair $x_i^t = \{n_i^t, \epsilon_i^t\}$.

The timing of the model is as follows:

1. Short-lived, non-strategic entrants choose to enter or not. If they do not, they vanish.[6]

2. Firms observe their public states $n_i^t$ and their private shocks $\epsilon_i^t$.

3. Firms simultaneously choose actions $a_i^t$

4. Patients choose their facilities according to the model above.

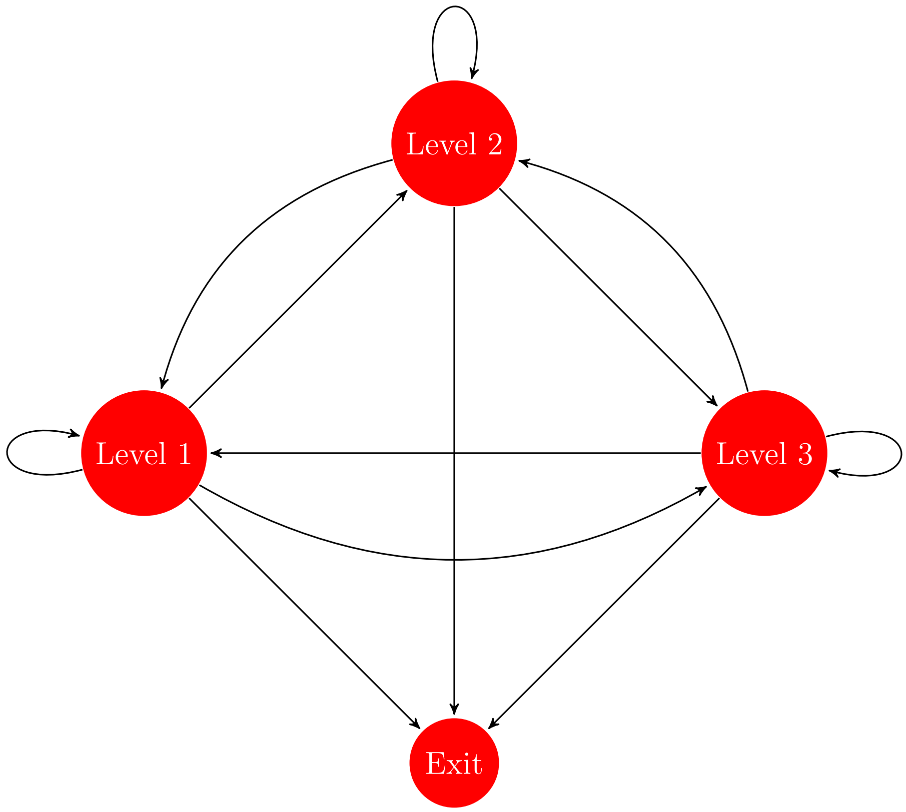
5. Firm payoffs $\pi_i^t$ are realized

6. Facility changes occur and patients information about changes to existing facilities and any new entrants is updated. Firms which exit realize a scrap value.

I permit entry of an entirely new hospital into the market in the model, though entry is not observed frequently in the data. I suppose that each period in each county

[6]There is no "optimal waiting" to enter the market.

there is one non-strategic potential entrant, who can decide to stay out, or enter at Level I, II or III. Entrants are drawn for each county in the state separately. (This is the only part of the model in which county geography matters - all other modeling and computation choices reflect actual distances, not county boundaries.) I use the empirical probabilities of entry from the data to inform this part of the model. Each hospital that enters a county is randomly assigned a location in the market in the county. This permits the computation of a distance to each relevant zip code. Entrants are assigned a number of beds equal to the mean bed number over facilities in the market. These characteristics are fixed. Hospitals which enter the market become available to patients, so their entry can affect the demand for the other facilities that remain in the market. In subsequent periods they have the option to make the same investment, divestment or exit decisions that hospitals actually in the data make.




Firms face demand, which is a function of mutable features of their facilities (i.e., whether they have Level I, II or III facilities). Several features which affect demand are treated as immutable: the total number of beds and the firm's location with respect to patients. Patient demand is computed according to the model estimated above in Equation (1.1) for every period. Patients' deterministic utilities for each hospital are updated every time any facility in one of their choice sets changes. Patients' choice sets are also updated to reflect entrants. During every simulation period, patient demand is computed across the entire state. Demand for each hospital is summed up at the DRG level across all patients who have the hospital in the choice set. Different patients in the same zip code can choose to go to hospitals which are not in the same county market, depending on their utilities, DRGs and private shocks. Firms realize profits separately from serving the two insurance types of patients. Firm variable profits are given by

$$\pi_i(x_{i,t}, x_{-i,t}) = VP_{i,t}(x_{i,t}, x_{-i,t}) + \epsilon_{i,t}$$

$$= VP^P(x_{i,t}, x_{-i,t}) + VP^M(x_{i,t}, x_{-i,t}) + \epsilon_{i,t}$$

where $VP^M$ and $VP^P$ denote the variable profits due to Medicaid and privately insured patients, respectively. The hospital pays a cost to treat each patient which is determined by that patient's DRG and which is the same across both categories of patients.

Since actual transacted prices are not observed in this setting, I also use the choice model to understand what effects investment has on the patient's willingness-to-pay (WTP) for access to the hospital (for WTP see [111] and [24]). The WTP measure is motivated by a model in which patients choose insurance networks ex-ante, prior to the realization of any health states. With a simple logit demand model for patient choice of hospital, an expression for the aggregate WTP of any (location, health state) pair is readily computed. The derivation which follows is very close to that of [24]. The discrete choice model above in (1.1) gives the patient's utility from hospital choice as a function of several demographic and clinical indicators. The utility of patient $i$ from choosing hospital $g$ among the set $G$ is given below. This result can be found in [24] or [5]. Conveniently, the expression for the expectation of the maximum value has a closed form, making the assumption that the error terms $\epsilon_{ij}$ are distributed Type-I Extreme Value, two useful results follow.:

$$\begin{aligned} WTP(G, X, \lambda) = & \quad \mathbb{E}\left[\max_{g \in G} \bar{U}_{i,g}(H_g, X_i, \lambda_{i,j}) + \epsilon_{i,g}\right] \\ = & \quad \ln\left[\sum_{g \in G} \exp\left(\bar{U}_{i,g}(H_g, X_i, \lambda_{i,j})\right)\right] \end{aligned}$$

Furthermore, the probability that patient $i$ chooses a particular hospital $j$ is given by the standard formula

$$s_j = \frac{\exp\{U(H, X, \lambda)\}}{\sum_{g \in G} \exp\{U(H, X_i, \lambda_i)\}} \tag{1.7}$$

This is also interpretable as the market share of patients of type $(X, \lambda)$, or the share of patients of clinical and demographic type X who live at location $\lambda$. The second useful result is that a solution for the utility given by the maximizing choice of hospital among the set $G$ can be derived in closed form.

[24] use this expression to derive an expression for the WTP of a patient $i$ of type $(X, Z, \lambda)$ to pay for the inclusion of hospital $k$ in the network of her insurer. They treat this expression as one component of the surplus over which insurers and hospitals bargain. Aggregating over all patient types, including demographics $X_i$, clinical characteristics $Z_i$, and locations $\lambda_i$ gives a composite measure of WTP for the complete set of hospital services over patients in the market defined by $G$ (which is not constant across patient types). This aggregate WTP for hospital $k$ is one component of the surplus over which insurers and hospitals bargain (the other component, not relevant or modeled here, is the reduction, or not, in cost to the network from including hospital $k$).

$$\mathbb{E}\left[\max_{g \in G} U(H,Y,X,\lambda) + \epsilon_{ig}\right] - \mathbb{E}\left[\max_{g \in G-\{k\}} U(H,Y,X,\lambda) + \epsilon_{ig}\right] \tag{1.8}$$

$$\ln\left[\sum_{g \in G} \exp\left\{U(H_g,Y,Z,\lambda_i)\right\}\right] - \ln\left[\sum_{g \in G-\{k\}} \exp\left\{U(H_g,Y,Z,\lambda_i)\right\}\right] \tag{1.9}$$

$$= \ln\left[\sum_{g \in G-\{k\}} \frac{\exp(U(H,Y,Z,\lambda)}{\sum_{g \in G} \exp(U(H,Y,Z,\lambda)}\right]^{-1} \tag{1.10}$$

$$= \ln\left[\frac{1}{1 - s_k(H_k,Y,Z,\lambda)}\right]^{-1} \tag{1.11}$$

The interpretation of this expression is that the ex-ante willingness to pay of an individual $i$ of type $(X_i, Z_i, \lambda_i)$ for access to hospital $k$ is inversely related to the share of patients of that type at that hospital.

Willingness to pay is not the same as realized revenue. WTP is measured in patient utils, but it does reasonably approximate the market-level valuation for the hospital's services across patient types and locations. However, the hospital's profit function is reasonably predicted to be a function $f(.)$ of this measure. To simplify computation, I suppose that the function $f()$ of willingness to pay is linear in WTP: $f(WTP) = \alpha_t WTP(Z_i, Y_i, \lambda_i)$, and that this $\alpha_t$ is constant across patient demographic, clinical and location types. It is permitted to vary across the level of the hospital facility. $\alpha_t$ converts patient utils to dollars.

The hospital's cost function $c(Z_i, Y_i)$ depends on patient clinical and demographic types, but not on the patient's location. As noted above, hospital's serve two types of patients in this model: those with private insurance and those who are publicly insured under Medicaid. This is a very close to the data: about 90% of patients in the inpatient data are covered by one of these two types of insurance. Denote the patient volumes as $V^T(X_i, Z_i, \lambda_i)$, where $T = P, M$ for Medicaid or Privately Insured patients of a particular $(X_i, Z_i, \lambda_i)$ type. Medicaid prices for patients in traditional Medicaid are not chosen by the hospital, but are instead set administratively according to the patient's clinical type $Z_i$. For those in managed Medicaid, prices are bargained over by the patient's managed Medicaid provider. These prices (and whether any individual patient is in managed or traditional Medicaid) are both unknown, so I treat these patients as being the same for reimbursement purposes. Then the hospital's profit over patient demographic types $Y_i \in Y$, clinical types $Z_i \in Z$ and locations $\lambda_i \in \Lambda$ can be written:

$$\begin{aligned}\pi_k = \sum_{z_i \in Z} \sum_{y_i \in Y} \sum_{\lambda_i \in \Lambda} \left(f(WTP(H_k, Z_i, Y_i, \lambda_i)) - C(Z_i, Y_i)\right) V^p(Z_i, Y_i, \lambda_i) \\ + \left(\bar{P}(Z_i) - C(Z_i, Y_i)\right) V^m(Z_i, Y_i, \lambda_i)\end{aligned} \tag{1.12}$$

The reimbursements actually paid by Texas Medicaid to hospitals for treatment of patients within the DRG's of interest are available from the Texas Health and Human Services Commission, so I treat them as known in the model. I take the mean costs within DRG as the realized amount of reimbursement for that DRG.

In the data, I observe facility level changes at a yearly frequency, so each decision period is one year. Each period, a hospital can decide to upgrade or downgrade its facility (depending on its current level). Hospitals can also decide to either keep their current facility or to exit the market. The hospital makes this decision after it has realized demand for the period. If it does change level, the facility is upgraded or downgraded and will start attracting new patients in the following period. Hospitals can also decide to exit the market entirely, shutting down and receiving some scrap value. A hospital must pay some transition costs when it changes level, given by:

$$C(a_{i,t}, a_{i,t-1}) = \mathbf{1}_{\{a_{i,t} \neq a_{i,t-1}, a_{i,t}=j, a_{i,t-1}=j\}} \Psi_j^k$$

I make the assumption that the cost can vary across the patient's health status $Z_i$ (i.e, a DRG) and the level of the hospital's facility. Cost parameters depend on the patient's DRG and the level of the hospital's facility. Denote the set of DRG's by $Y$. Then the cost function takes the form:

$$C(Z_i, Y_i) = \sum_{y_i \in Y} \sum_{l=1}^{3} \mathbf{1}_{\{y_i=d, l=k\}} \gamma_{y,k} \tag{1.13}$$

Combining the terms above, the per-period profit function is

$$\begin{aligned}\pi_k = \sum_{z_i \in Z} \sum_{y_i \in Y} \sum_{\lambda_i \in \Lambda} \left( f(WTP(Z_i, Y_i, \lambda_i)) - \sum_{l=1}^{3} \mathbf{1}_{\{d=i, l=k\}} \gamma_{i,k} \right) V^p(Z_i, Y_i, \lambda_i) \\ + \left( \bar{P}(Z_i) - \sum_{l=1}^{3} \mathbf{1}_{\{y=i, l=k\}} \gamma_{i,k} \right) V^m(Z_i, Y_i, \lambda_i)\end{aligned} \tag{1.14}$$

The fact that the profit function is linear in the parameters to be estimated greatly eases the computation burden. This modeling strategy is frequently pursued in this literature, e.g., [95]. Under this assumption, the value function can be approximated once and values easily computed under a variety of parameter values without redoing the approximation.

## 1.6 Estimation/Empirical Strategy

The estimation strategy is based on [9]. In the first stage, I recover estimates of the probabilities of the three behaviors: investment, divestment, or exit. In the second stage, I use the estimated probabilities to compute approximations to the value function under equilibrium and non-equilibrium strategies. I recover the parameters by minimizing the set of deviations from the equilibrium conditions.

For each market-year I simulate 500 Monte Carlo approximations of the value function, in which each approximation draws 40 simulated years. In each period, potential entrants decide to enter or not at the beginning of the period. If entry occurs, the entering hospital will not realize any demand until the next period. This can be interpreted as a time-to-build constraint: it takes one year to build and staff a new hospital.

Since the profit function is linear, the simulation can be run once. A set of parameter values minimizing the criterion function can be found. I recover the parameters using the Laplace-type estimator of [26]. The criterion function is in [9]:

$$Q_n(\theta, \alpha) := \frac{1}{n_I} \sum_{k=1}^{n_I} \left(\min\left\{\hat{g}(X_k; \theta, \alpha), 0\right\}\right)^2$$

where the function $\hat{g}$ is $\min\{V(\sigma;\theta) - V(\sigma';\theta), 0\}$. $V(\sigma;\theta)$ and $V(\sigma';\theta)$ are approximations of the value function estimated from the equilibrium behavior $\sigma$ and a perturbation of that equilibrium behavior $\sigma'$. $\theta$ is a vector of parameters to be estimated. To form the simulated policy functions, I take the equilibrium policies and perturb them by a small $\epsilon$. The assumption that the observed behavior represents a Markov Perfect Nash equilibrium means that we must have $V(\sigma;\theta) \geq V(\sigma';\theta)$. Parameters are chosen to minimize the violations of that constraint over all hospitals in the model

### 1.6.1 First Stage: Policy Functions

In the first stage, I estimate the firm's probability of investing, divesting, exiting or remaining where it is as a function of the firm's state: its own level and the levels of its neighbors, as outlined in the model section above. I impose a logit functional form on the firm's choice and include a polynomial in the state variables ([10]). I use the model of behavior so obtained to simulate firm behavior in response to arbitrary investment behaviors by competitors or new entrants.

### 1.6.2 Estimation Results

The first set of estimates I recover are the per-patient per-DRG costs of an admission. The magnitudes are reasonable. I compare them to two other sets of available information. First, I obtained DRG-level reimbursement under Texas Medicaid for every hospital in the state. I report the values for 2012, which is the last available year. The values here are the average payment hospitals actually received and the number of patients treated in that DRG for the whole state. The second set of values is from Truven Health Analytics. The data reported here is for Austin, TX only and for 2014 which is the only set of data available to me. The reimbursements reported are DRG-level for only the set of employers which provide data to Truven. This is the only data available to me on private insurance reimbursements for these services in Texas.

The specific pregnancy-related DRGs[7] for which the costs are estimated are:

1. $\gamma_{385}$ - "Neonates died or transferred"
2. $\gamma_{386}$ - "Extreme Immaturity/Respiratory Distress"
3. $\gamma_{387}$ - "Prematurity w/ Major Problems"
4. $\gamma_{388}$ - "Prematurity w/out Major Problems"
5. $\gamma_{389}$ - "Full-term Neonate w/ Major Problems"
6. $\gamma_{390}$ - "Neonate w/ Other Significant Problems"
7. $\gamma_{391}$ - "Normal Newborn"

The estimated parameter values follow in Table (1.14). The estimates are reasonable because, for the most part, the estimated costs lie in between the Medicaid values and the private insurance values.

One of the central trade-offs in this market is that, while hospital entry may disperse volume and lead to worse outcomes, it might also lower prices through increased competition. If that is the case, then individuals may end up receiving a slightly lower-quality service, but they may also pay less for it. It appears that additional competitors do not lower hospital's profits for NICU services in an appreciable way. Hospital profits are decreasing only slightly or perhaps not at all as the number of competitors increases. This suggests that hospitals

[7]The $\gamma$ parameters are numbered according to their actual DRG numbers given by CMS.

| $\gamma$ | Value (Lev. 1) (Lev. 2) (Lev. 3) | Std. Err. | Texas Medicaid Mean/(Var.) (2012) | TX Med. N | Truven Health Mean/(Var.) (Austin, 2014) | Truven N |
|---|---|---|---|---|---|---|
| | 20680 | 7285 | | | | |
| | 42692 | 6326 | 12044 | 2267 - | 34232 | |
| $\gamma_{385}$ | 20962 | 6355 | (19162) | 2731 | (93482) | 9 |
| | 81918 | 18347 | | | | |
| | 74193 | 18409 | 45323 | 3965 - | 172357 | |
| $\gamma_{386}$ | 99065 | 18575 | (31888) | 4269 | (258559) | 55 |
| | 30405 | 26172 | | | | |
| | 49801 | 36150 | 15751 | 2891 - | 34690 | |
| $\gamma_{387}$ | 22376 | 26096 | (11659) | 3219 | (49802) | 64 |
| | 10051 | 1211 | | | | |
| | 19019 | 1289 | 4413 | 6217 - | 18412 | |
| $\gamma_{388}$ | 33963 | 1351 | (3997) | 6553 | (43618) | 42 |
| | 29122 | 1257 | | | | |
| | 14279 | 1236 | 6330 | 6333 - | 10283 | |
| $\gamma_{389}$ | 20708 | 1235 | (7946) | 6673 | (38945) | 338 |
| | 22830 | 755 | | | | |
| | 6754 | 786 | 1529 | 22339 - | 3756 | |
| $\gamma_{390}$ | 3667 | 716 | (1885) | 22711 | (4504) | 383 |
| | 9089 | 684 | | | | |
| | 8120 | 683 | 570 | 106178 - | 2045 | |
| $\gamma_{391}$ | 3667 | 659 | (534) | 106474 | (1065) | 638 |

Table 1.14: Parameter Values

still have considerable power vis-a-vis the insurers they bargain with, at least for NICU services.

Estimated entry costs follow in Table (1.15). The facility investment costs estimates are less precisely estimated than other parameters, because the investment decision modeled here is a coarsening of the actual investment decisions that firms contemplate. The firm's decision would be more accurately modeled as the choice of a level and a size (a number of beds).

Table (1.22) records the sizes of NICU facilities every 2 years for my sample period. The standard deviation in facility sizes is large relative to the mean, as is the difference between the maximum and minimum sizes in the sample. The costs associated with adjusting the number of beds in a NICU up or down may be marginal relative to the cost of the whole facility, but there are still substantial unmodeled cost differences between building a NICU of two beds and building one of 118 beds. This modeling choice is needed to keep the size of the state space manageable.

The choice of 3 NICU facility levels, plus an exit state, gives four total choices for each period. By contrast, supposing that hospitals make level and size choices with only three size options (e.g.,'small', 'medium' and 'large') for levels 2 and 3 leads to a tremendous increase in the size of the state space.[8] To minimize the complexity of computations, I restrict firms to a coarser strategy.

[8]The size of the state space is discussed more completely when I compute the counterfactuals.

| Parameter | Value | Std.Err. |
|---|---|---|
| $\alpha_1$ | 829 | 285 |
| $\alpha_2$ | 36166 | 6326 |
| $\alpha_3$ | 16309 | 6355 |
| $\Psi_{1,2}$ | 1937550 | 1881520 |
| $\Psi_{1,3}$ | 4937363 | 1881526 |
| $\Psi_{1,EX}$ | -6218 | 36125 |
| $\Psi_{2,1}$ | 82164 | 93623 |
| $\Psi_{2,3}$ | 2062763 | 2006142 |
| $\Psi_{2,EX}$ | 3497 | 93623 |
| $\Psi_{3,1}$ | -1700590 | 193879 |
| $\Psi_{3,2}$ | -163005 | 21983 |
| $\Psi_{3,EX}$ | 31229 | 36342 |

Table 1.15: Willingness to Pay ($\alpha$) and Fixed Investment Costs ($\Psi$)

## 1.7 Identification

The parameters to estimate are the $\alpha_i$ terms, which multiply WTP for each of the three levels, the $\gamma_{i,k}$ terms which represent firm costs of treating patients at different DRG's, levels and insurance types and the $\Psi_{k,l}$ terms which capture the fixed costs of level changes or exiting. Part of the model identification comes from the fact that the underlying returns to investment are changing differentially across the state as the population grows, while the number of new hospitals is stable or declining. For example, from July 2014 to July 2015, the population of the state increased by 490,000.[9] 84% of this increase happened in just four metro areas: Houston, Dallas-Fort Worth, Austin and San Antonio.[10] The population of

[9] US Census Bureau, 2016.

[10] These are the top four metro areas by population in the state. There are 25 metro areas in total. The other 6 in the top 10 are McAllen-Edinburg-Mission, El Paso, Corpus Christi, Brownsville-Harlingen, Killeen-Temple-Fort Hood, and Beaumont-Port Arthur, the smallest of which has around 400,000 residents.

Houston (excluding the metro area, 2012 population 2.1 million) increased by 24% between 1990 and 2012, while San Angelo (2012 population 96,000) increased by 14% over the same period. These increases are observable at the zip-code level in inpatient admissions data. The population of Texas grows substantially over the period studied in this paper: from 17 million in 1990 to about 26 million in 2012. This changes the returns to the investment for hospitals differentially depending on their location.

The coefficients $\alpha_i$ multiply WTP, which is computed at the zip-code level for each patient type. WTP varies not only with investments made by firm $k$, but with any investment, entry or exit decisions made by any competitor accessible from any of the zip codes from $k$ that attracts patients (recall that patients are permitted to choose among the 10 closest hospitals to their zip code, provided that distance does not exceed 50 miles). The responsiveness of willingness-to-pay for a given hospital $k$ also varies across zip codes $z_i$ and $z_j$ depending on both their distances from $k$, and the set of competitors of $k$ that are accessible to patients from that zip code. Distant zip codes in opposite directions from the same hospital generally have different choice sets. WTP is computed directly in each period for each zip code, so the total willingness to pay across all patients who might choose a given hospital is known.

In the diagram below, Figure (1.1) this idea is illustrated in a simplified fashion. Each circle represents all patients in each market for the three hospitals $A, B$ and $C$. The intersections of the circles are subsections of markets (zip codes) shared by more than one firm. When hospital $A$ changes from level 1 to level 3, all of its patients change their WTP for hospital $A$. However, total WTP for hospital $A$ also varies with the decisions made by hospital $B$ in regions $(A, B)$ and $(A, B, C)$ and with the decisions of hospital $C$ in regions

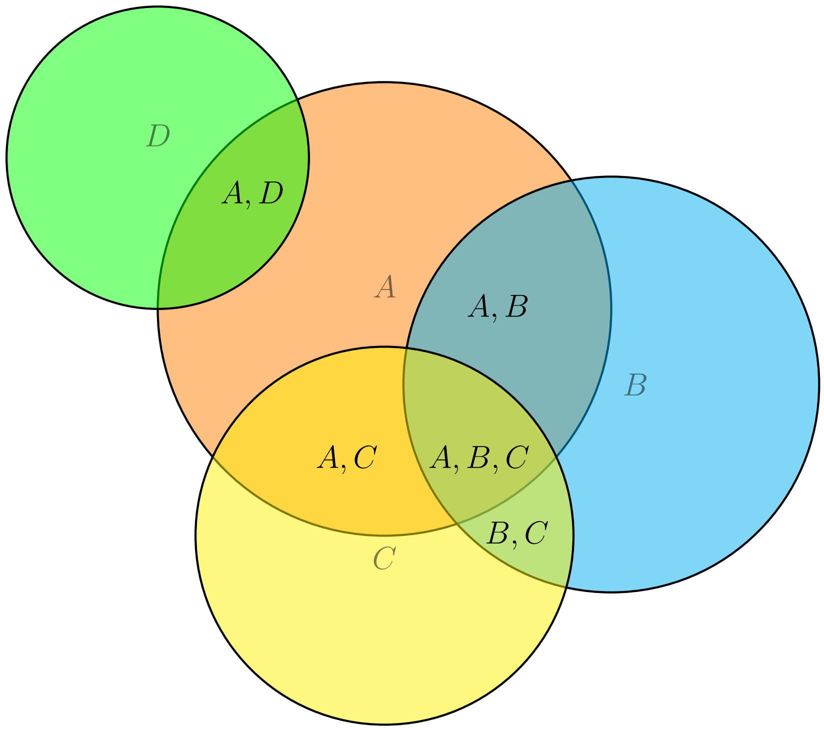



Figure 1.1: Illustrating Changes in Willingness to Pay

$(A, C)$ and $(A, B, C)$. The individual decisions of hospitals $A, B$ and $C$ to invest or divest all affect the aggregate willingness to pay for the other two hospitals. However, the decisions of hospitals $A$ and $D$ each only affect the other, since they share a market not shared by the other two facilities. This diagram is a simplification, since of course the distances involved in real examples are not likely to be so large that it is impossible for a patient to drive past $D$ to seek service at $B$.

Patient volumes are computed directly in each period from the estimated choice model. Patient choices respond to investment: patients prefer higher level facilities and are aware when hospitals make changes in the levels of the NICU facilities. Patients in different DRG's and of different insurance types can respond differently to investment decisions,

| Levels | Mean Change (%) | Change SD | Max Change | Min Change |
|---|---|---|---|---|
| 1 to 3 | 160 | 38 | 212 | 38 |
| 1 to 2 | 103 | 21 | 131 | 29 |
| 2 to 3 | 28 | 6 | 34 | 11 |
| 2 to 1 | 51 | 6 | 56 | 30 |
| 3 to 2 | -20 | 3 | 25 | 9 |
| 3 to 1 | -60 | 7 | 67 | 35 |

Table 1.16: **Table of Changes in WTP from Changing Own Level**

facilitating the identification of the $\gamma_{i,k}$ terms, which vary by DRG.

The identification of the fixed costs of a hospital changing levels is best explained with a simplified version of the model, similar to that in ([29], Appendix.) Suppose that the components of the profit function are identified by the previous argument, so that I can write the profit as a function of the firm's level, e.g., $\pi(i)$. In a two-level problem, the firm at level 1 should invest if:

$$\pi(1) + \frac{\beta\pi(2)}{1-\beta} \geq \Psi_{1,2}$$

and remain at its current level if

$$\frac{\pi(1)}{1-\beta} \geq \pi(1) + \frac{\beta\pi(2)}{1-\beta} - \Psi_{1,2}$$

I suppose that the cost $\Psi_{1,2}$ is the same across markets for all level 1 hospitals. Profits $\pi(1)$ and $\pi(2)$ depend on the distribution of patients in each market, so the different investment decisions of level 1 hospitals suffice to identify $\Psi_{1,2}$ in this simplified example. A similar argument can be made for the model with three level choices.

## 1.8 Counterfactuals

In the following two sections, I describe two sets of counterfactuals I run with the models estimated in this paper. The first set of counterfactuals require only the results of the static model. In this set of simulations, I allow a social planner to impose facility restrictions within markets.

### 1.8.1 Static Counterfactuals

One of the main counterfactuals I run involves a hypothetical social planner who determines which hospitals will be permitted to have NICU's. This affects patient decisions about which hospitals to choose, the volume of NICU patients in each hospital, and the distribution of revenues among hospitals. Importantly, running this counterfactual does not require that any hospital solve a dynamic optimization problem. The investment 'decision' is not made by the hospital itself, but is assigned to it. This can be compared to the perinatal regionalization program in Portugal ([80]) or the regionalization of stroke care in London ([77]).

The first step is a baseline simulation, which takes the current market structure as it is given. Patients are assigned to their hospitals according to the choice model. Once assigned, they draw birth weights for their infants according to the observed probabilities in the NCHS data. Mortality rates for very low birth weight infants at each hospital are determined according to the estimates using Texas birth certificate data. Patient mortality is calculated for the entire state.

There are then two versions of Certificate of Need programs: in both every market (here defined as a county) is constrained to have a single Level III facility. In one version, patients who show up at other hospitals (all level I by construction) who draw very low birth weight infants are treated at the facility where they arrive. No patients are transferred. The increase in patients at the single Level III facility comes from the preferences patients have for higher level facilities ex-ante.

In the second version, patients who arrive at a hospital without a Level III facility and realize a VLBW infant are transferred to the single Level III facility. The origin facility loses some revenue associated with that patient, while the destination facility gains revenue. The Level III improves its outcomes treating all VLBW patients due to realizing a higher patient volume equal to the total number of VLBW patients in the market. These two possibilities are an upper and a lower bound on the effects of regionalizing and concentrating volume. An actual regionalization program would inevitably have less than perfect compliance with a transfer program and some patients might die in transit.

These two counterfactual arrangements are not unrealistic when compared to existing CON regulation schemes. Some CON regulation schemes do restrict Level III services to a single facility in a large district, as in New York State. New York is divided into seven regions of 1 - 14 counties. Each block outside of New York City generally has one or two high-level "regional" intensive care centers. Transfer arrangements are quite successful in perinatal care and mortality is very low. California (which does not regulate NICU investment via CON) has a public system to track the availability of open beds in NICU's at each hospital in the state in real time.[11] The time taken to transfer is unlikely to be an issue for most

[11] For Northern California, see http://www.perinatal.org/BedAvailability.aspx?region=nocal and for Southern California, see http://www.perinatal.org/BedAvailability.aspx?region=socal

| Counterfactual | 1 | 2 |
|---|---|---|
| | CON | CON |
| Description | Monopoly | Regionalization |
| $\Delta$ Mortality | 156 | 219 |
| (Variance) | (31) | (26) |
| $\Delta$ Profit | $-3.7 \times 1e6$ | $-2.8 \times 10e6$ |
| (Variance) | (2.45e6) | (3.8e6) |
| $\Delta$ HHI | 132 | 299 |
| (Variance) | (27) | (60) |

Table 1.17: Static Counterfactual Results

patients, since labor has long average duration.[12]

### 1.8.2 Dynamic Counterfactuals

The other set of counterfactuals requires the set of dynamic parameters estimated earlier. First I will describe the two solution procedures applied.

#### 1.8.2.1 Solving the Dynamic Model

I apply two methods to solve the model. The first is the exact solution outlined in [85]. This method works well because the state space of the model is not very large in smaller markets: each firm can be in one of 4 states (Levels 1-3 and the exit state). There are $4^N$ possible market configurations in each market with $N$ firms, where N is the total number of firms within 25 miles. Since firms are symmetric, and since the state varies depending on distance, the number of distinct states is lower. For example, in a three hospital market,

[12]There are three stages: the infant is born during the second and the placenta is discharged during the third. Early labor lasts 8-12 hours, and active labor 3 - 5. Labor is considered precipitous when the child is born within less than three hours of the onset of regular contractions. This affected about 2.5% of all births in the US in 2010.

suppose that hospitals A, B and C are all at level 1. Suppose that hospitals B and C are each 10 miles from A. From the point of view of Hospital A, the state is the same when Hospital B has level 2 and Hospital C has level 3, and when Hospital C has level 2 and Hospital B has level 3. When updating the value of each aggregate state, I cycle through all possible configurations of the state of each hospital in the market. The number of configurations of $n$ hospitals over $k$ possible states, when the number at each state is constrained to be non-negative, is given by $\binom{n+k-1}{n}$.

The most time-consuming part of the computation is updating the deterministic component of the utility of consumers for each different configuration of states. When markets are small enough that the update does not take much time for each iteration, I iterate over all possible states at each iteration and compute the value of all of them. Convergence is judged by checking the distance between successive iterations of the algorithm. When the increase is small enough, convergence is achieved. I use $10^{-5}$ as my convergence criterion. To my knowledge, there are no algorithms akin to value iteration that guarantee convergence in this type of model, but when an equilibrium is found, it can be verified.

Once a firm has more than 5 and fewer than 10 neighbors I compute the value approximately, rather than exactly. For these markets, I apply the methods of [86]. Intermediate sized markets include Austin and San Antonio. For larger markets, the number of total states grows very large very fast as the number of neighboring hospitals increases. There are two obstacles to computation: the size of the full state (all $4^n$ configurations) is too large to hold in memory as a set of tuples of (Hospital ID, State) once there are more than 14 neighbors. Furthermore, the time taken to update the deterministic component of utility for all zip codes accessible from each hospital is too high. This makes an approximation method necessary.

#### 1.8.2.2 Dynamic Simulation Results

The results of the baseline simulation in both the exact and approximated cases are as one would expect. For nearly every firm, the value of being in its actual state exceeds the value of its other options. For those firms which are not in their highest-valued state, generally upgrading is more profitable than downgrading. Conditional on keeping the set of competitors identical, I find that most firms' actual state is its maximizing state. When firms' competitors exit the market, a firm may find it profitable to upgrade.

Results from the Austin market are in Table (1.18). The hospitals with much higher values are more centrally located and see more patients as a result. The single Level II facility in the metro area also has a lower value. Brackenridge, which is a "safety net" hospital which sees a much higher Medicaid, uninsured and Travis County hospital district (i.e., indigent) population, has the lowest value among the three centrally located facilities (St David's, Seton Med. Center and Brackenridge).

Patient revenue changes driven by level changes can be decomposed into two factors: an increase in the number of patients, and a change in the composition of patients. From the patient choice model, we know that general obstetrics patients value NICU services, which is visible in Figure (1.7). However, the possibility of admitting patients to the NICU means that hospitals will also earn more revenue on average from each patient, driven by the subset of patients who are admitted to the NICU.

| Hospital | Level (2016) | Value $\times 10e8$ |
|---|---|---|
| St David's Medical Center | III | 9.00685951 |
| St David's South Austin Medical Center | II | .01797498 |
| Seton Medical Center | III | 1.5370150 |
| Seton Northwest | III | 0.1727939 |
| Seton Southwest | III | 0.1335213 |
| Brackenridge | III | 3.0653228 |

Table 1.18: Hospitals in Austin, TX

#### 1.8.2.3 Increasing Investment Costs

In my second counterfactual, I simulate the evolution of a market under rapidly increasing investment costs. The goal of this exercise is to achieve a regulatory regime somewhere between strict CON control and the existing free entry equilibrium. In principle, a wide range of tariffs could be imposed by the social planner. In a somewhat more sophisticated example, the planner could estimate a choice model similar to the one proposed above, and could simulate the counterfactual flow of patients across facilities under different facility configurations, including the flow of VLBW patients. With this model, the planner could predict how much patient volumes will shift in the event of entry into the market. A planner could then account for the volume effects of shifting patients around, and could charge a fee to the potential entrant. This would force an entering hospital to internalize the costs which entry would impose on its patients.

A simpler option for the regulator is to assess a fixed fee for each new entrant, which is increasing in the number of facilities in the market. This fee would depend on the volume effects, but would not take into account the specific flows of patients or the locations of hospitals relative to the larger population. In the simulation here, I do the latter. This permits me to keep the fee schedule the same across markets and saves time in computing what would otherwise be hospital-specific investment fees. In principle, other options are available to the planner.[13]

The results are as one might expect: increase fees steeply enough and hospitals can be dissuaded from investing, despite the large increases in revenue which follow from their doing so. At some point, the costs of investment plus the fee exceed the continuation value to the firm of the additional facility, so the firm prefers to stay where it is. One of the costs of this arrangement to patients can be measured in additional miles driven for two populations: additional patients who choose the higher-level hospital ex ante, and a smaller subset of patients from elsewhere in the market whose infants are transferred to the high level facility.

I can compute the average distance driven to hospitals under any market configuration. This is accomplished by measuring the distance from the zip-code centroid to whatever hospital is chosen for each person in the zip code. Aggregating up over the whole market permits measurement of the average distance driven by everyone. Average distances are both not very large initially and do not vary much when configurations are changed. This is because most patients live in urban areas which are compact and hospitals frequently are centrally located. When levels are changed, only a fraction of patients choose different facilities, the additional distance they travel is not that great, so the average distance traveled over the whole market does not change very much. For example, forcing all hospitals but one in the entire Austin market to *exit* increases the average population-weighted distance

[13] In Neonatal Intensive Care, Florida (which has strict CON controls) employs an explicit formula and targets bed numbers regionally on that basis, see [2], p. 11

| County / City | N | Average Distance |
|---|---|---|
| Travis / Austin | 7 | 14.6 |
| Harris / Houston | 30 | 8.7 |
| Bexar / San Antonio | 10 | 14.45 |
| Dallas / Dallas | 16 | 10.0 |
| Tarrant / Fort Worth | 11 | 12.2 |
| El Paso / El Paso | 6 | 10.9 |

Table 1.19: Average Distances Driven by Market

| County / City | N | Equilibrium Distance | Alternate Distance |
|---|---|---|---|
| Travis / Austin | 7 | 14.6 | 15.8 |
| Harris / Houston | 30 | 8.7 | 8.9 |
| Bexar / San Antonio | 10 | 14.45 | 14.35 |
| Dallas / Dallas | 16 | 10.0 | 10.3 |
| Tarrant / Fort Worth | 11 | 12.2 | 11.8 |
| El Paso / El Paso | 6 | 10.9 | 10.7 |

Table 1.20: Average Distances Driven by Market Under Different Configurations

traveled by about one mile. The population-weighted average distance to a hospital in Houston assuming that all individuals choose among their ten closest options is 11 miles. Values are recorded for several large metro areas in Table (1.19).

Under alternative configurations, average distances traveled barely change. Additional patients do choose to go to the higher-level NICU, but the additional distance they travel is not so great. In Table (1.20) I show the distances traveled under the prevailing market conditions and distances traveled under one market arrangement with centralized service provision.

Note that Table (1.19) suggests that average distances traveled (on a population-

| Market | Maximum NICU Admits - Any Month 2005-2012 | Highest Annual Monthly Average 2005 - 2012 | Largest NICU |
|---|---|---|---|
| Bexar | 357 | 309 | 94 |
| Dallas | 352 | 301 | 91 |
| El Paso | 162 | 130 | 20 |
| Harris | 616 | 565 | 118 |
| Tarrant | 297 | 262 | 62 |
| Travis | 167 | 144 | 67 |

Table 1.21: Max NICU Admits in Any Month, 2005 - 2012

weighted basis) are low in all metro areas. They stay low when NICU services are centralized. What this suggests is that extremely implausible travel costs must be assumed to make the welfare change from this change negative overall.

#### 1.8.2.4 Relaxed Merger Enforcement

For this counterfactual, I suppose that pairs of hospitals merge, but consolidate their facilities. That is, I suppose that all VLBW infants who show up at one facility are transferred to the other. The combined facility then benefits from the volume of patients showing up at each separately. As described above, this is quite a reasonable assumption within urban areas: distances are small and the duration of labor is long. I do not observe mergers in the data and cannot identify parameters relevant to determine when and why they occur, so I specify the merging firms, rather than permitting firms to endogenously choose their merger partners. The absence of any price observations is a limitation in this exercise, but with that in mind, I do keep track of the willingness to pay of the merged firm.

In the following table, I report the results for several large Texas counties under an exogenously given merger specification. The results are consistent with what one might ex-

| Year | Mean NICU Size (Beds) | SD | Minimum | Maximum |
|---|---|---|---|---|
| 1990 | 15 | 11 | 2 | 60 |
| 1992 | 17 | 11 | 1 | 60 |
| 1994 | 17 | 13 | 2 | 72 |
| 1996 | 16 | 12 | 1 | 72 |
| 1998 | 19 | 14 | 2 | 60 |
| 2000 | 20 | 14 | 2 | 60 |
| 2002 | 20 | 15 | 2 | 68 |
| 2004 | 22 | 17 | 2 | 76 |
| 2006 | 22 | 18 | 2 | 90 |
| 2008 | 24 | 21 | 4 | 92 |
| 2010 | 25 | 21 | 3 | 94 |
| 2012 | 24 | 21 | 2 | 118 |

Table 1.22: Mean, Standard Deviation, Minimum and Maximum NICU Beds, 1990 - 2012

pect given the symmetric treatment of hospital NICUs: mortality declines as facility volume increases due to consolidation. Merging two hospitals allows the merged facility to realize the mortality gains associated with the combined volume of the two facilities. In expectation, this saves several lives annually. The specific identities of the merging firms do not matter, given the symmetric treatment of all NICUs. Distances traveled increase only slightly, as in Table (1.20). Mergers do increase pricing power and travel distances, but likely not to the extent that the next welfare change is negative. A proxy for the change in pricing power can be derived from the change in the WTP of patients for the merged firm's services. That is reported in percentage terms in the last column of Table (1.23). Even supposing that the prices the firms charge increase in the same percentage as the change in WTP, prices are not so high that the net welfare effect is negative.

This suggests a different regulatory concern with respect to mergers in markets where

| Market | Sum of Pre-Merger Mortalities | Mortality Post-Merger | WTP % Change Rel. to Max Prior |
|---|---|---|---|
| Travis / Austin | 15 | 11 | 13% |
| Bexar / San Antonio | 17 | 11 | 29.4% |
| Harris / Houston | 17 | 13 | 54% |
| Tarrant / Fort Worth | 16 | 12 | 23.8% |
| Dallas / Dallas | 19 | 14 | 54.7% |
| El Paso / El Paso | 20 | 14 | 58.4% |

Table 1.23: Pre-merger and Post-merger Mortality in Large Markets

quality is increasing in consumer volume. Firms claim increased efficiencies and lower costs, but firms and regulators should also consider the possibility of quality improvements. Moving down the curve in quarterly patients admitted to the NICU in Figure (2.1) cuts the probability of mortality by two thirds. Ultimately, the positive effects on quality may be even more important than the efficiencies gained through cost reduction.

#### 1.8.2.5 Unmodeled Features

Two unmodeled feature of the present counterfactual are (1) the potential for congestion in a high-demand service under entry restrictions and (2) the endogeneity of hospital/doctor effort.

To put the first problem another way, how large does a hypothetical single NICU have to be in Houston to handle the volume of patients at its highest? As noted earlier, most facilities in most months do not approach their capacity constraints. This would likely be different under strict CON regulation. Admissions evidence suggests that most facilities are not very close to their capacity constraints. Table (1.21) lists the maximum number of admitted in any given month, the highest monthly average admits in a county over the years

2005 - 2012 and the largest NICU in the county.

The endogeneity of doctor's effort is a more important problem. Producing quality outcomes takes an inputs of patients, as argued above, but it also takes effort by the doctors themselves. The incentives for a monopoly provider of NICU services to exert effort might be considerably reduced by strict CON regulation of entry. The optimal regulatory response to the volume effects in large markets is probably a small oligopoly of competing facilities, rather than a single monopoly provider.

## 1.9 Conclusion

In conclusion, this paper attempts to understand the incentives for hospital investment in advanced technologies and the resulting consequences for aggregate welfare in a market characterized by increasing returns to quality in consumer volume. In my context, the results suggest that considerable savings in lives can be realized from centralizing services and/or restricting further entry into the market. This is, moreover, not likely to come at a high cost in patient welfare due to increased costs of travel, since almost all of the volume of patient deliveries (and so almost all of the volume of very-low birth weight infants) is concentrated in a relatively small group of highly populated urban areas with many hospitals where travel distances are already low. Population-weighted average distances traveled barely change under a variety of market arrangements. Implausibly large per-mile travel costs are required to outweigh the additional costs due to increased mortality. The market power gained by restricting hospital investment in this service area to a few firms is substantial, however, as shown by the increase in the HHI. This will affect the distribution of surplus between the patient's insurer and the hospital itself, and some of the increase in costs will be passed through to the patient herself.

Free entry into this market has an unexpected and high cost. While the inability to observe prices charged is an important limitation of the data available, the expected increase in mortality due to decreased patient volumes across facilities likely swamps all of the potential gains due to lower prices from increased hospital competition. The key feature of this market: that conditional on staff and technologies, the patients themselves are a crucial input to the learning by doing process for which no substitutes exist, suggests that regulators should take a different attitude towards entry regulation. Rather than considering entry something which is inevitably good, a full accounting of the costs and benefits of entry requires recognizing and weighing the costs of decreased patient volume and the increased mortality which results. The results in this market suggest that entry restrictions are warranted, that mergers may have positive effects beyond increased efficiencies and that, on the whole, competition among facilities for these patients has negative consequences.

## 1.10 Appendix

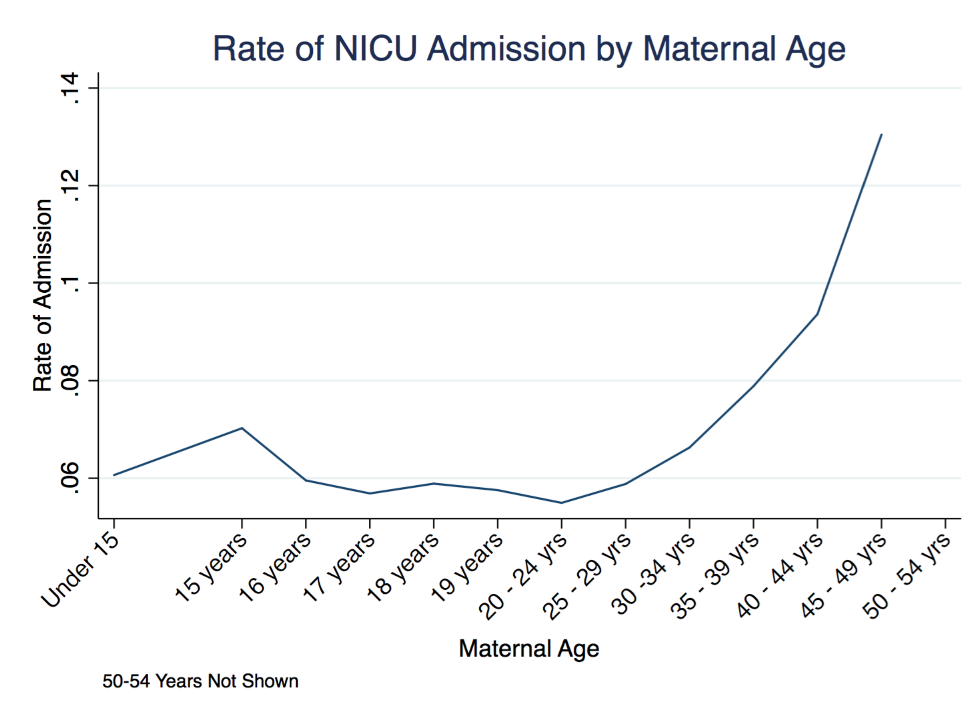



Figure 1.2: NICU Admission Probability at Different Maternal Ages

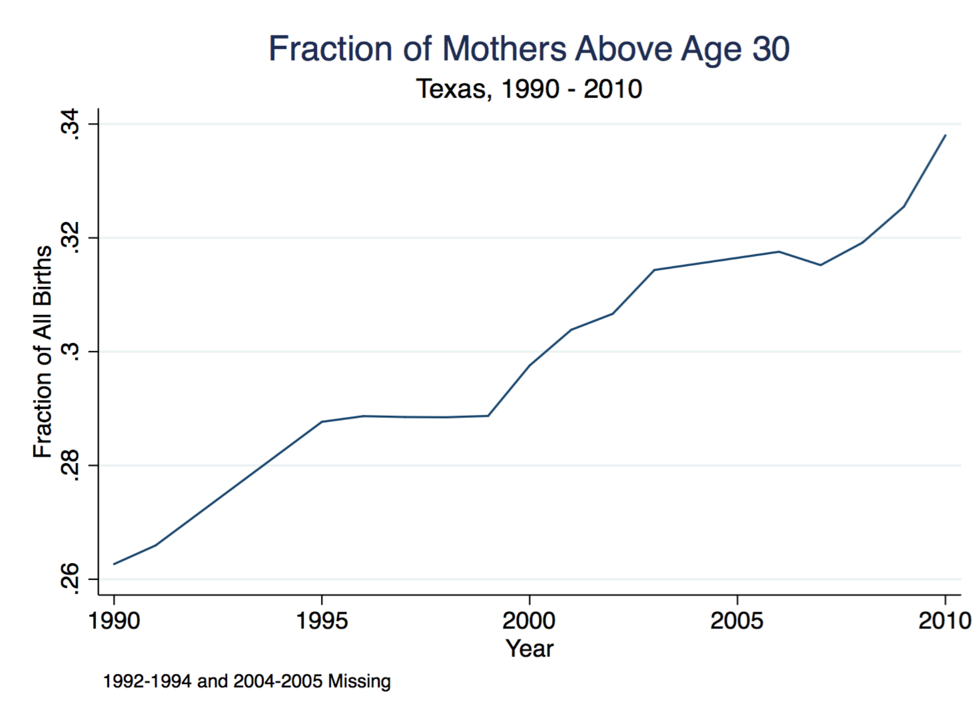



Figure 1.3: Fraction of Mothers Above age 30 in Texas

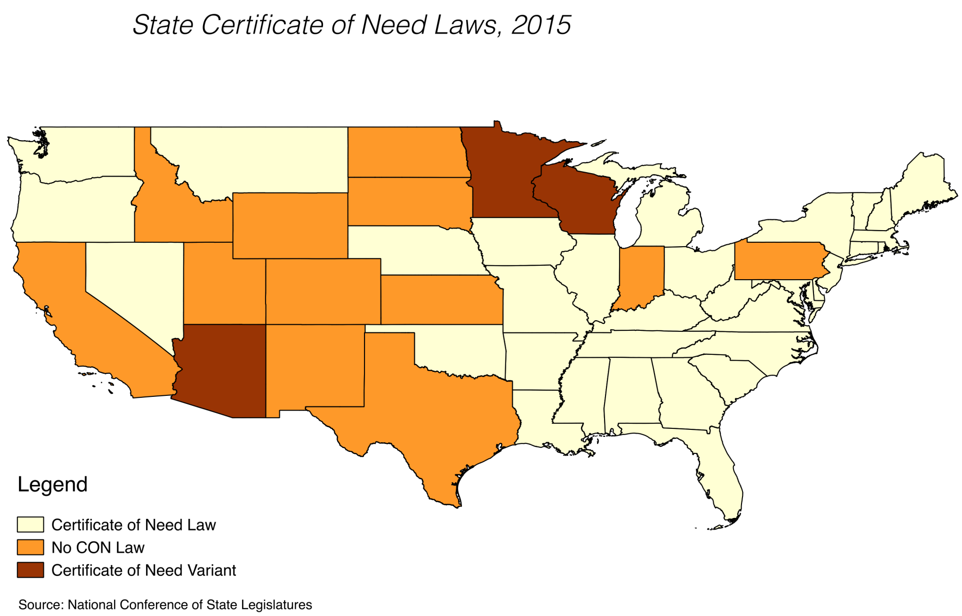



Figure 1.4: State Certificate of Need Legislation

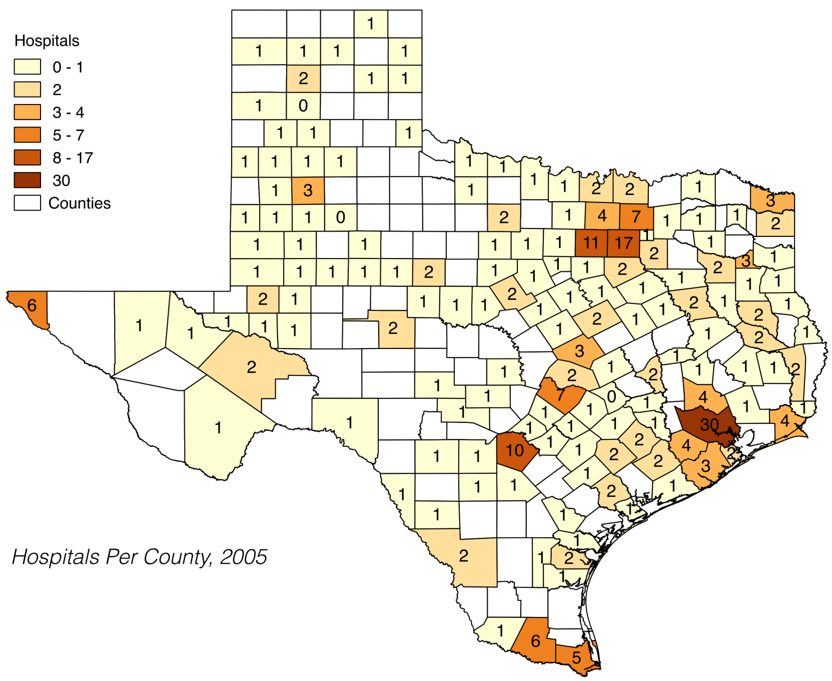



Figure 1.5: Hospitals Per County, 2005 Data

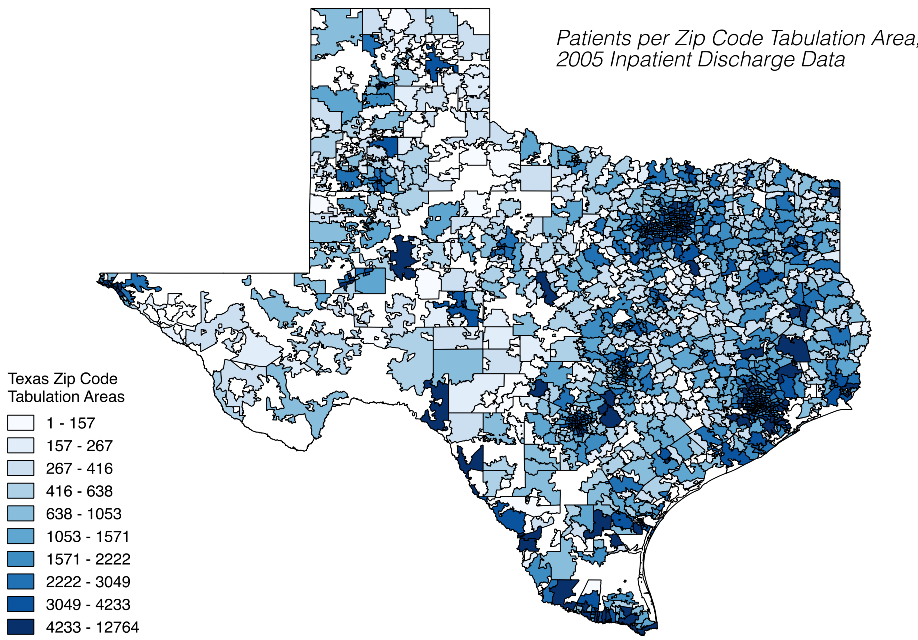



Figure 1.6: Population Density at the Zip Code Level

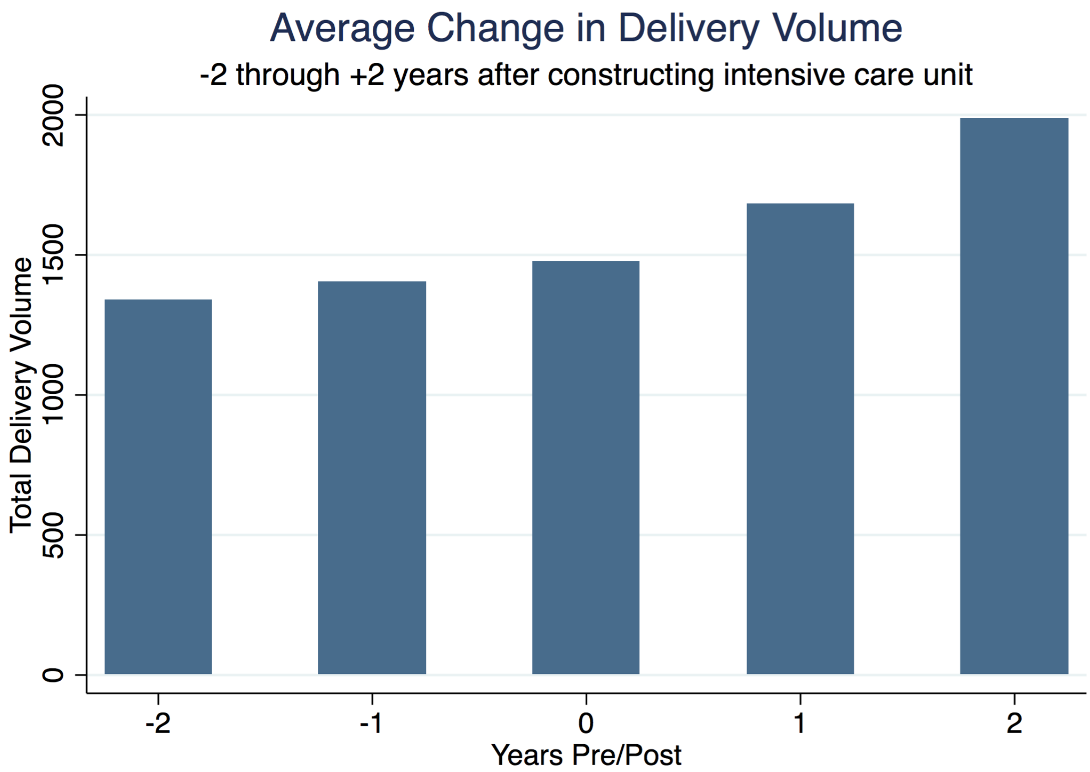



Figure 1.7: Delivery Volume Changes in Texas Hospitals

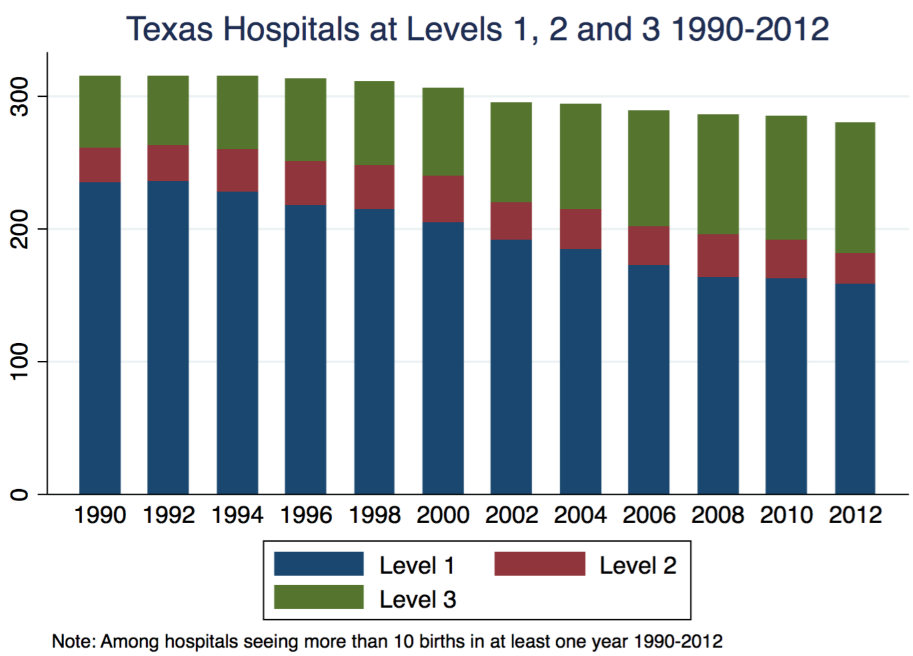



Figure 1.8: NICUs Across All Texas Hospitals

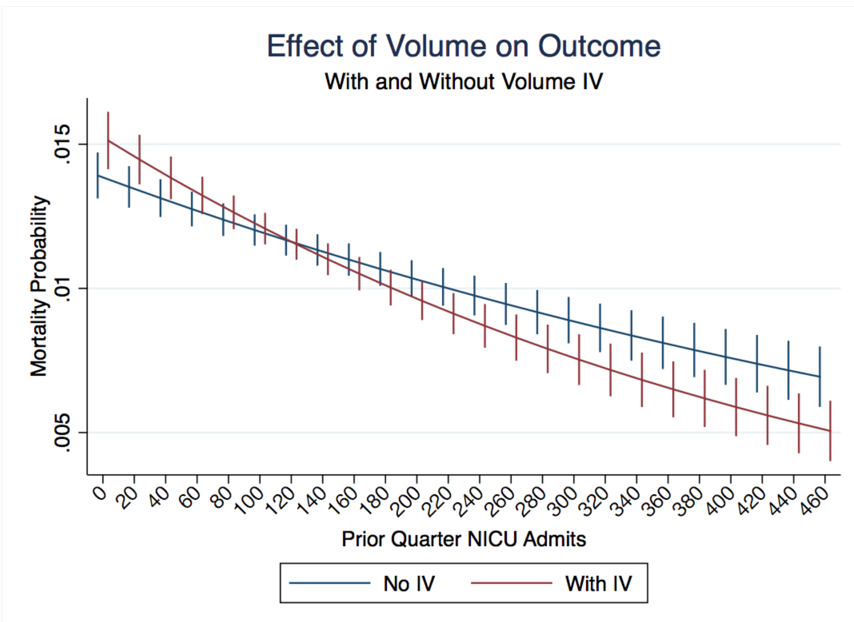



Figure 1.9: Partial Effects of Volume on Mortality Probability

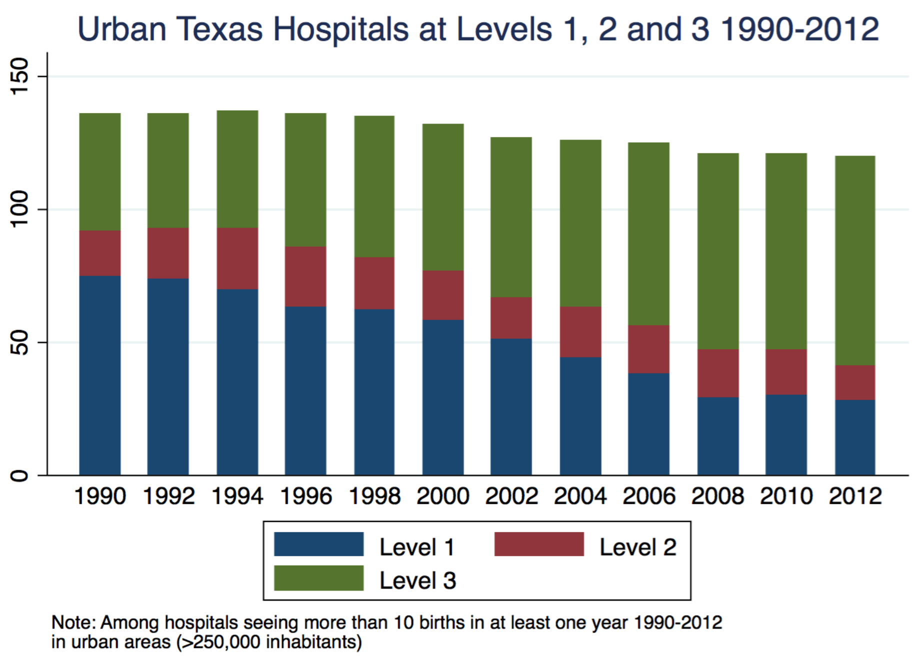



Figure 1.10: NICUs in Counties with More than 250,000 Residents

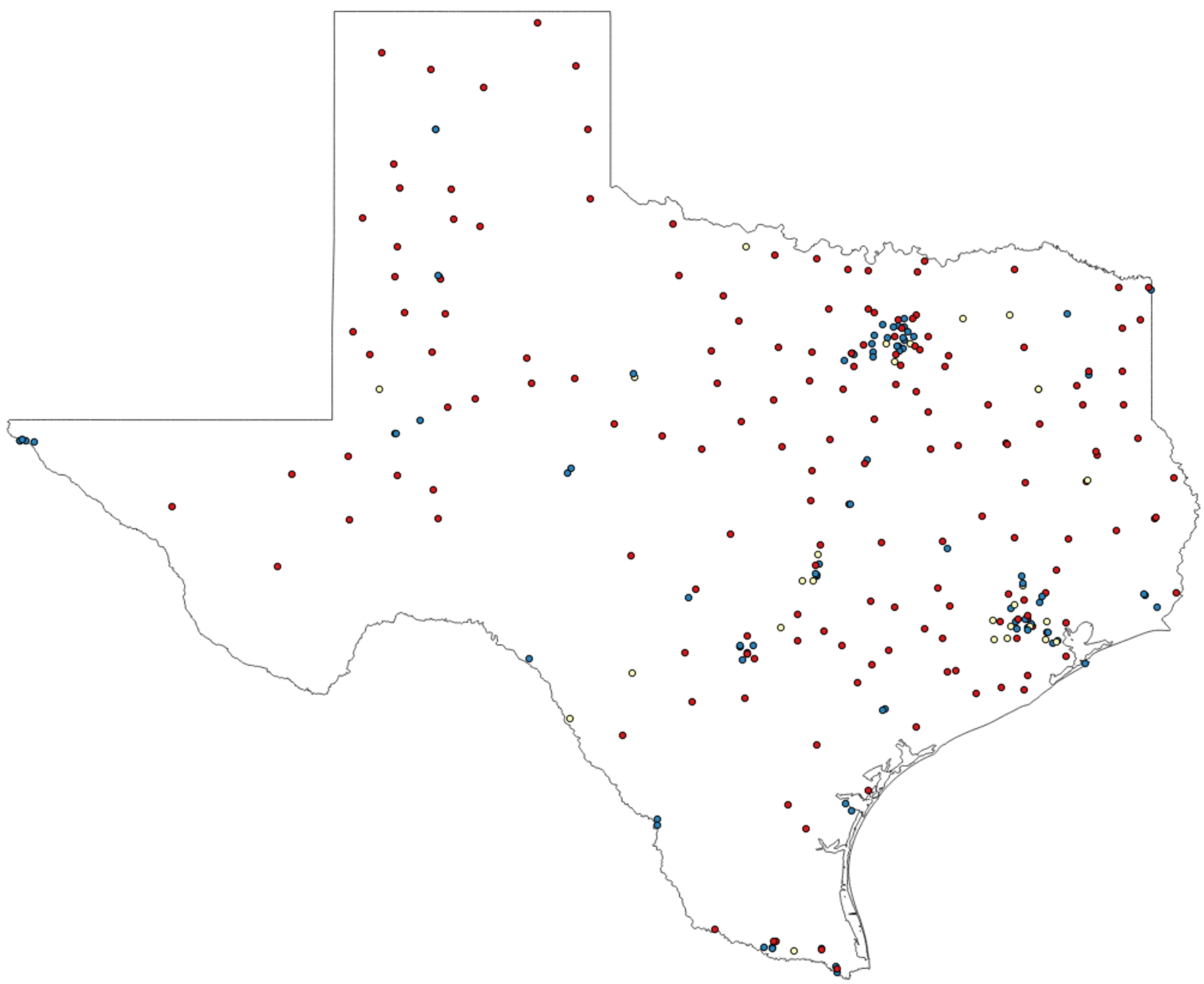


Figure 1.11: Geographic Distribution of Hospitals

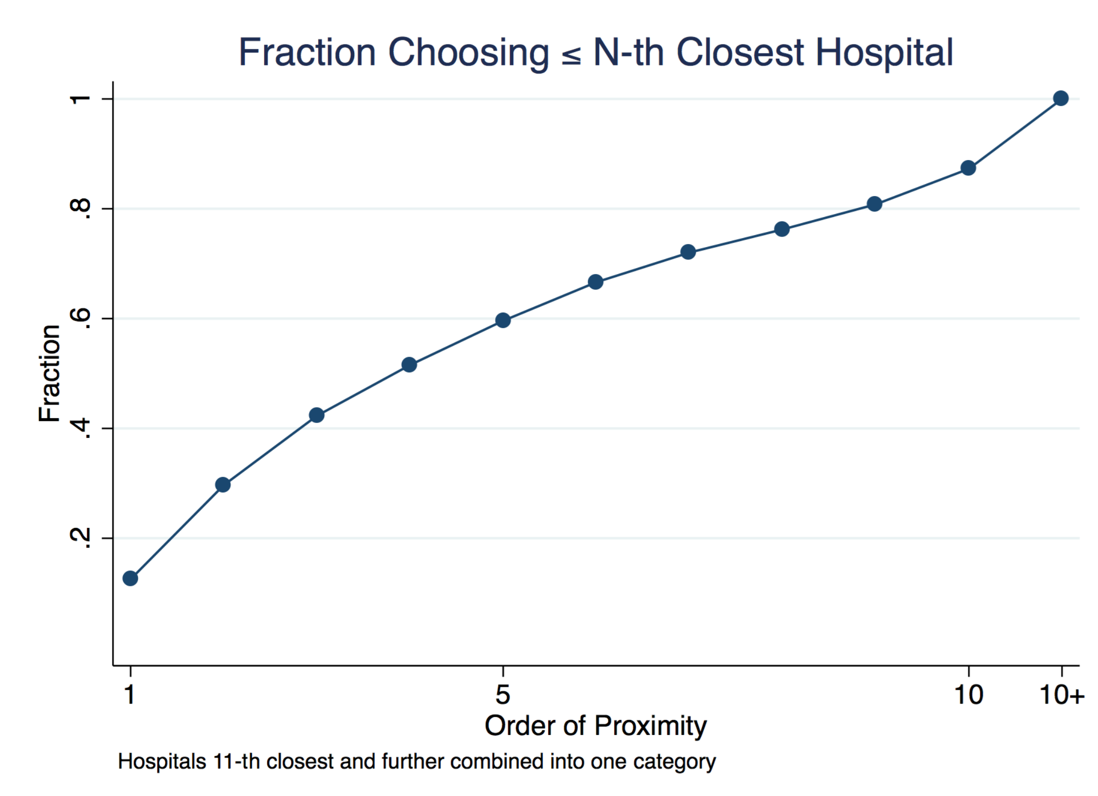



Figure 1.12: Fraction Choosing Closest

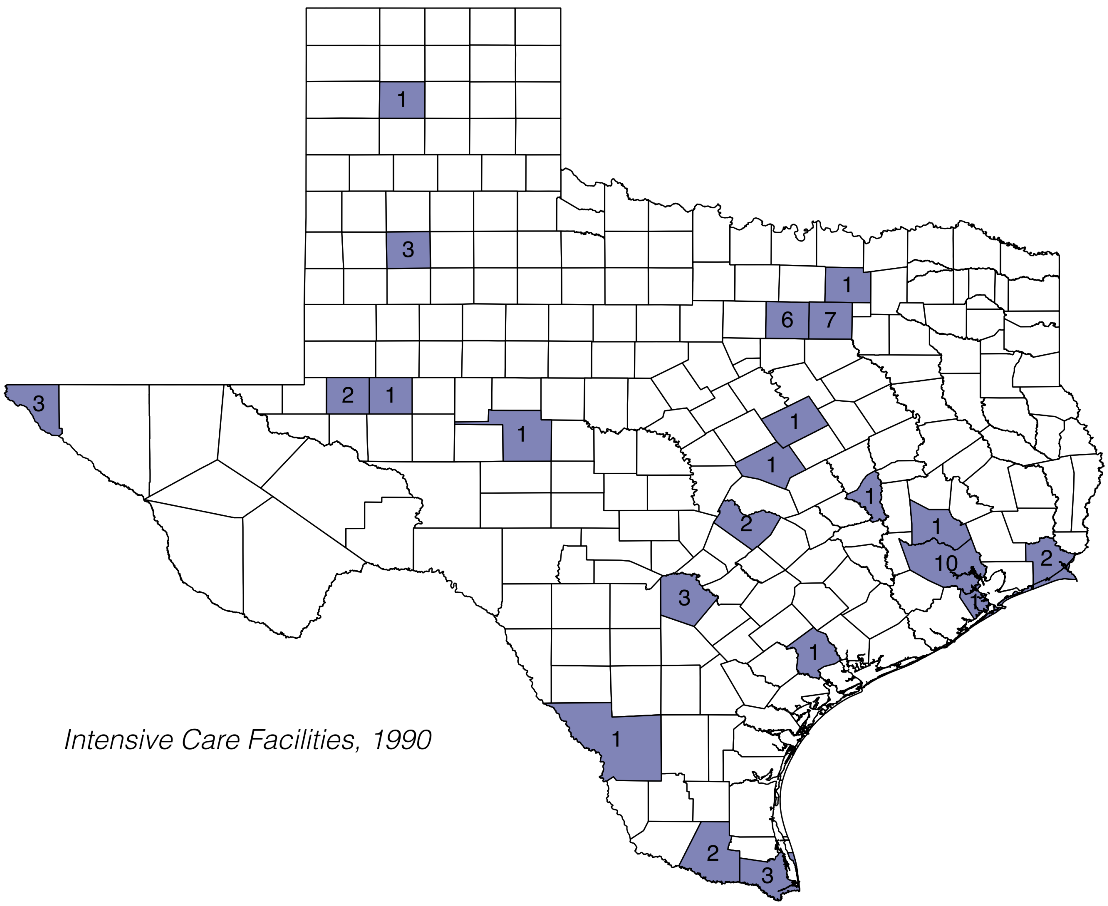



Figure 1.13: Intensives in 1990

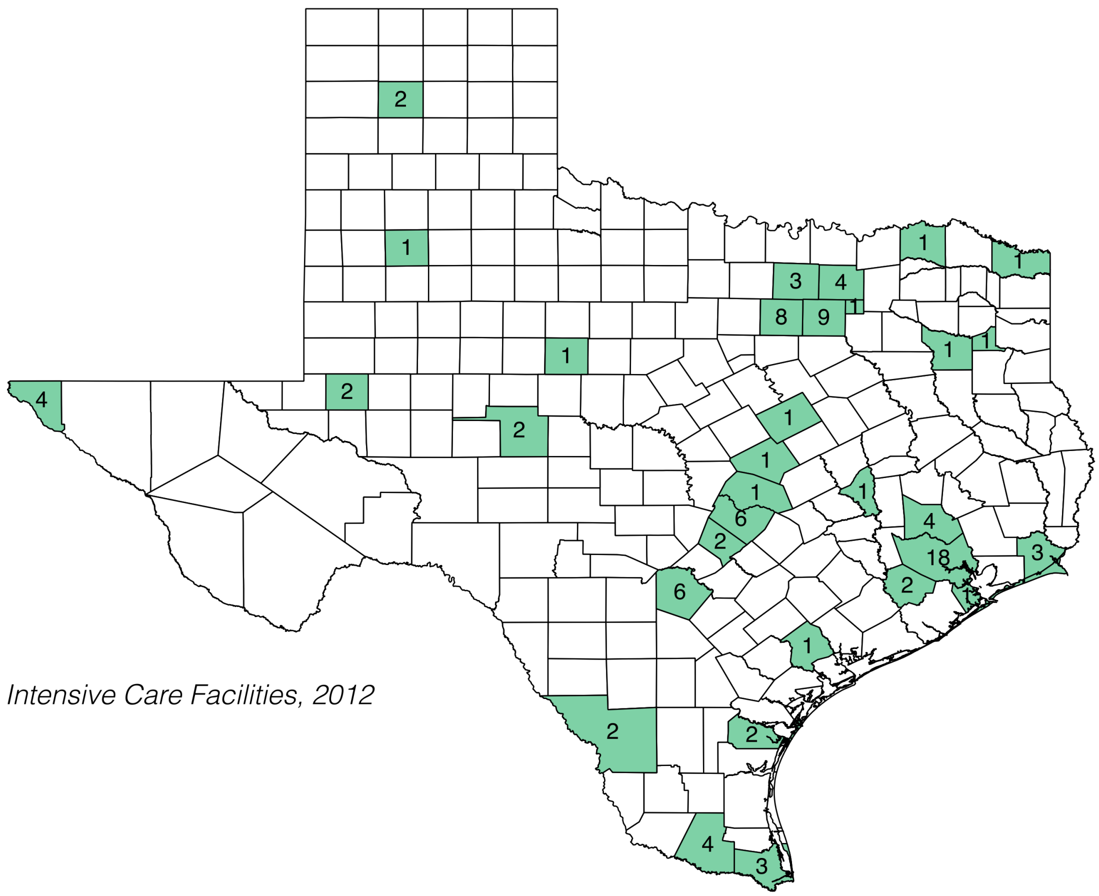



Figure 1.14: Intensives in 2012

# Chapter 2

# Volume Outcome Relationships in Texas Neonatal Intensive Care

## 2.1 Introduction

Studies of the impact of surgical or procedure volume on the quality of outcome are numerous across a wide array of medical procedures. [88] consider the question in the context of neonatal intensive care in California and finds that infants treated in the highest-volume and highest-level facilities in the state have a significantly (in the statistical and economic sense) lower probability of mortality. The current paper takes a similar approach to the question using Texas data, but I extend the work of Phibbs and coauthors using new data and several different approaches to recover an underlying causal effect. Existing work on this question both in the context of neonatal intensive care (and more broadly in other areas of medicine) suggests that there are important positive effects on the quality of outcomes which result from being treated at a NICU in a hospital which admits large numbers of patients to the NICU.

The leading explanation for these effects in the medical literature is that learning by doing occurs at the hospital level. Doctors and who see more patients understand better the complexities involved in treating them. This is naturally plausible to those who work in the field, but is also supported by empirical evidence from other work on learning. An equally important effect which evidence in this paper suggests is at work here is organizational forgetting. When doctors and nurses do not see as many patients, their skills degrade and the mortality rate increases. Patient volume not only matters, but needs to be consistent to ensure that knowledge gained by experience does not depreciate. Organizational forgetting is the subject of several studies, including [17] and [35]. [64] study the effects on mortality at the individual-doctor level of a doctor's absence from the operating room, whether due to days off or extended vacations, and find that being away from the operating room raises the likelihood of mortality for the patients who see the doctor after she returns. This suggests that it is important to make sure that doctors see sufficiently many patients on an ongoing basis.

This question is of central importance, especially to the population of very low birth weight infants ($<$ 1500 grams at birth). Very low birth weight infants account for roughly 1.5% of all infants born every year, but more than 50% of all infant deaths annually in the United States. Nearly all are admitted to NICU's at birth and generally form a substantial fraction of those admitted. About 55% of all patients admitted to NICU's in Texas are low birth weight ($<$ 2500 grams), while 16.5% are very low birth weight. Lowering the mortality rate by a significant amount for this population has the potential to generate huge welfare gains, given that each additional life saved counts at the full value of a statistical life. A beneficial side effect would be to lower the infant mortality rate in the US, which lags rather far behind that of most other advanced economies.

The current paper adds to the existing literature in several ways. First, by employing IV techniques to control for the endogeneity of patient volume, I am able to more credibly estimate the causal effect of volume on outcome. Second, the data I employ permits me to make more precise inferences about the timing of the volume of patients admitted to each NICU than has been possible in previous literature. Specifically, I can condition on the volume of patients admitted in the previous month since I observe all patients who are admitted plus any transfers.

Also, using monthly observations on the month of birth permits me to compute a measure of the stock of accumulated experience at the level of a single facility, including both patients who were admitted at birth and who were transferred in. This permits me to answer two questions. First, how important is more vs. less recent lagged volume in reducing the mortality rate? Second, if more recent volume is more important than more temporally distant lagged volume, what is the implied depreciation rate of the stock of accumulated knowledge? This is key to addressing whether forgetting exists in this setting and, if so, what the magnitude of the effect is.

Additionally, in this paper I attempt to infer the underlying distribution of unobserved quality of the hospital, given the observed choice and mortality data. I follow [53], who employ Bayesian methods using data on hospital admissions for pneumonia in hospitals in Los Angeles County.

For a preview of the results, consider the plot in Figure (2.1). In this figure, I plot the effect of volume on patient mortality from a probit including facility and year fixed effects, where all other variables are evaluated at their mean values in the sample. The y-axis records the probability of death as lagged one-quarter patient volume varies across the x-axis. The range of patient volumes is chosen to be the 5th through 95th percentiles of quarterly NICU admissions in Texas. What is immediately visible from the graph is that the effects of additional volume in the previous month lowers the probability of mortality.

The two lines show the effect of volume on outcome with and without corrections for the endogeneity of patient volume, but the conclusion is the same in both settings: higher volume facilities produce better outcomes for patients. With the IV results, it is possible to express greater confidence that the effect is truly causal, rather than merely the result of selective referral.

I further investigate the way that these effects change with time. I estimate a probit model for mortality including 12 separate monthly lags, capturing an entire year's lagged volume. I find that the importance of lagged monthly volume to subsequent mortality outcomes declines rapidly with time. Almost all of the effect is driven by the most recent two months, while later months appear to have no impact at all on the quality of the outcome. This suggests that the rate of depreciation of knowledge in NICU's is quite high. I estimate rates of knowledge depreciation which are substantially higher than those found in [17]'s study of the production of airplanes.

The consequences for total patient mortality from moving all infants in the state from facilities at the lower end of the volume distribution to the highest are large. The total number of patients admitted to NICUs in the lowest quarter of the patient volume distribution annually is around 6,000, of which 120 die annually. The estimation of the effect of volume on outcome suggests that some fraction of these patients could potentially be saved if they were initially sent to higher volume facilities. For example, taking all patients across all Texas counties and sending them to the highest volume facilities in their counties would say an estimated 146 lives annually. Valuing each statistical life at $7,000,000, which is a median given existing estimates (see [117]) leads to a total welfare gain of $1,000,000,000. Those gains are quite substantial. Concentrating the increase in volume across neighboring counties (e.g., transferring from suburban to urban hospitals) would increase this figure even more.

Overall, the conclusion I draw is that there are likely "too many" NICU's in Texas. While competition among hospitals may lower prices and increase the convenience of access for patients who are able to visit new NICU's closer to their homes, the fact that the volume of patients needing the service in the state is roughly fixed from year to year means that most NICU's in the state operate at low volumes. (For direct measurements of capacity utilization, please see [15].) Lower patient volumes result in higher mortality rates than could be achieved with fewer facilities. Patients in the aggregate would be better off driving longer distances to one of a smaller number of facilities than they are in the current market equilibrium.

An outline of the rest of the paper follows. In Section II, I cover the related literature on studies of volume on the quality of outcome, on learning by doing and organizational forgetting, and on Bayesian estimation of firm-specific quality. In Section III, I provide some brief background about Neonatal Intensive Care Units and the populations which they serve. Section IV briefly reviews the data. Section V covers the estimation of the volume-outcome relationship with and without an instrument for patient volume, while section VI covers two approaches to estimating a forgetting rate. Section VII includes a Bayesian analysis of hospital-specific quality. Section VIII covers the policy implications and welfare consequences. Section IX concludes.

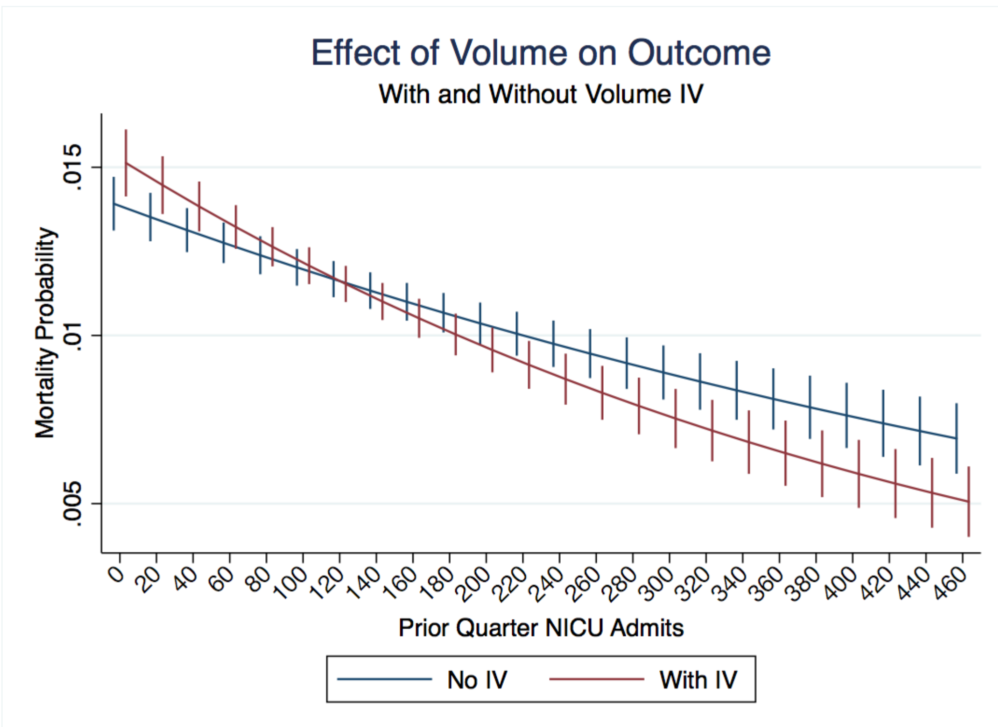



Figure 2.1: Partial Effects of Volume on Mortality Probability

## 2.2 Related Literature

Studies of volume and outcome in the context of medical care are numerous. For a broad survey of results across different procedures, see [83]. Evidence exists across procedures suggesting that higher volume facilities produce better quality outcomes. Achieving credible identification of these effects is difficult, due to the endogeneity of patient volume. [69] outlines some of the difficulties in studying this question credibly. Nevertheless, the existing literature is large and suggests that effects run from volume to outcomes. Most of the papers in this literature do not address the underlying mechanisms at work. For a systematic review of work on that subject, see [76]. [63] is an example from the economics literature of a study of the benefits of *regionalization* - concentrating particular procedures into a smaller number of facilities.

Neonatal intensive care units can be divided into levels, generally numbered 1- 3, with 3 being the most sophisticated. There are at least two channels of interest in studies of infant mortality in the context of neonatal intensive care. First, there is a literature on the level of the facility to which an infant is admitted. Certain infants who would benefit from being treated in the highest possible level NICUs end up in lower-level facilities, perhaps due to a lack of information on the part of their mothers about the relevant differences among hospitals. This becomes more likely and more frequent as the number of lower-level (i.e., Level 2) facilities increases. This has been documented in [88] in the case of California. Whether due to insufficient information or some other factor, parents or doctors do not immediately transfer very low birth weight infants to the highest level facilities. As a result, mortality is higher than it should be among patients who remain in Level 2 facilities. Two further examples of this literature are [42] and [8], who come to somewhat different conclusions about the

| County | | Total Births | Total LBW | Total VLBW | % LBW | % VLBW |
|---|---|---|---|---|---|---|
| Travis | Mean | 21055 | 1745 | 349 | 8.3 | 1.6 |
| | St. Dev. | 1000 | 35.6 | 21 | 0.29 | 0.13 |
| Bexar | Mean | 30274 | 2959 | 525 | 9.9 | 1.7 |
| | St. Dev. | 749.5 | 92 | 32.5 | 0.18 | 0.08 |
| Harris | Mean | 74916 | 6857 | 1324 | 9.15 | 1.8 |
| | St. Dev. | 2728 | 333.6 | 68 | 0.15 | 0.06 |
| Texas | Mean | 404,259 | 34,264 | 5915 | 8.4 | 1.45 |
| | St. Dev. | 9559 | 998 | 200 | 0.05 | 0.05 |

Table 2.1: Mean Births, Low Birth Weight Births, Very Low Birth Weight Births in Several Large Texas Counties, 2005 - 2010

importance of the level channel in California and Pennsylvania, respectively. The current paper does not consider level effects in part because Level 2 facilities are less common in Texas. I focus exclusively on volume effects (i.e., the effect of being admitted to a higher volume facility, conditional on a level) rather than level effects.

The issue in this paper is that of patient volume at a given facility, rather than patients sorting into 'incorrect' facilities. Related literature in this area includes [88], [65], [66], [89]. The papers cited are all supportive of the idea that higher volumes lead to better quality outcomes, though none of them attempt to correct for the endogeneity of volume. I do in this paper using an instrumental variables strategy. [13] is a related paper looking at the impact of the diffusion of managed care on mortality rates in this market and investment in this service area by hospitals.

The instrument strategy I use is employed in [54] and in [45]. A related approach involving predicting HHI is employed in [68], though those authors do not use their generated

HHI measure to instrument for actual HHI. Those authors compute a predicted HHI across markets using observed patient shares at the zip code level, weighted by the importance of those shares to the hospital overall. Those authors do not use their measure to instrument for HHI, which is endogenous to firm conduct.

There is a literature on forgetting within organizations and its effect on outcomes. One of the best known papers in this literature is [17] who studies rates of forgetting in airplane production. He finds about a 4% monthly depreciation rate of the stock of accumulated knowledge. This is a similar rate to that estimated by [108], who studies forgetting in the production of Liberty ships during World War II. [107] and [110] study learning in the context of this same production environment. [64] and [35] study forgetting in the context of medical care. [64] study within-surgeon effects of time out of the operating room on patient mortality after patients return, while [35] study forgetting in the context of emergency medical care. [35] estimate about a 10% depreciation rate for the stock of accumulated knowledge every month. [33] find nearly full monthly depreciation of the stock of knowledge in pizza franchises. Observed rates of depreciation vary widely depending on the exact setting and method used. Rates of depreciation may be overestimated due to data limitations, especially job separation rates within an organization, which is a point made by [35].

Bayesian estimation of this type of model follows [53]. Employing a probit model of hospital choice with a data augmentation approach originally due to [3], [53] recover the underlying distribution of unobserved hospital quality. The posterior distribution which results from a discrete choice probit model was intractable prior to the application of the data augmentation approach in [3]. For a thorough discussion of the application of the Gibbs sampler to these problems, see both [50] and [49]. For a general overview, [27].

## 2.3 Industry Background

Neonatal intensive care units are distinguished by levels. Level I units are general obstetrics wards which do not provide any advanced services to sick infants, though can stabilize patients for transfer elsewhere. Level II units provide services beyond what are offered at Level I facilities, but do not perform surgery on neonates and do not offer mechanical ventilation of unlimited duration. (Many extremely premature infants are born with underdeveloped lungs, so infants born at Level II units must be transferred if they need artificial ventilation for an extended period of time.) Level III units are more advanced and less restricted than Level II units: they provide mechanical ventilation of unlimited duration, surgery for neonates and a wide range of advanced services for those in need. These definitions come directly from Texas' Department of State Health Statistics Annual Survey of Hospitals, administered jointly with the well-known Annual Survey of the American Hospital Association. Definitions are consistent across years.

The majority of patients who are admitted to NICU's at birth are admitted due to prematurity/low birth weight. Patients admitted to the NICU are generally born earlier and at lower birth weight than those not admitted. Differences among the population of patients admitted to the NICU vs. those not are in Tables (2.2), (2.3), and (2.4).

Empirical work on the effects of patient volume on quality suggest that the negative externality in production is large: on the order of a 20% increase in mortality from cutting volumes at a high-level facility in half ([88]). The volume of patients needing intensive care services (including low and very-low birth weight infants) in a hospital referral region is roughly fixed from year to year. Perhaps 8-9% of all infants will be low or very-low birth weight, for example, while the number of infants needing sophisticated treatment of other serious conditions is generally small. Table 2.1 contains counts of very low birth weight infants for four of the largest counties in the state between 2005 and 2010. The last row reports the values for the state as a whole (including the top three rows). Both the number and standard deviations of very low birth weight infants are low: out of 400,000 births in the state per year, around 6,000 infants will be very low birth weight, but the standard deviation of the size of that population is only 200 patients per year. The entry of an additional NICU and subsequent redistribution some of the volume from existing facilities to the new entrant may result in lower average volumes everywhere. Fewer opportunities to treat patients are available and skills degrade with time. This makes the outcomes for all patients worse, including those in both the new hospital and the existing hospital.

In Table (2.2), t-tests of the difference in mean values for several different variables measured at birth across those admitted and not admitted to the NICU. It is immediately clear that there are important differences across several variables. Birth weight among those admitted to the NICU vs. those not admitted differs by about 800 grams, or about 31% of the average for the population admitted. The difference is highly significant. Gestational age differs by about 3.5 weeks between the two populations: those admitted to the NICU spend on average almost a month less in the womb. Maternal weight gain differs by about half a pound, maternal age by about half a year and the number of prenatal visits by just over half a visit. While all differences are statistically significant, the birth weight and gestational age variable differences are large enough to make a meaningful difference in outcomes.

The differences by race follow the expected pattern. African-American mothers are

| | Diff | St.D. | Mean All | N | Mean NICU | N |
|---|---|---|---|---|---|---|
| Birth Weight | 800.828 | 1.200 | 3321.96 | 2850162 | 2521.13 | 230853 |
| Maternal Weight Gain | 0.496 | 0.047 | 34.52 | 2850162 | 34.02 | 230853 |
| Gestational Age | 3.450 | 0.007 | 38.91 | 2850162 | 35.46 | 230853 |
| Maternal Age | -0.408 | 0.013 | 27.63 | 2850162 | 28.04 | 230853 |
| Adeq. Pren. Care | -0.676 | 0.041 | 15.16 | 2850162 | 15.83 | 230853 |
| 5 Min. APGAR | 0.353 | 0.014 | 9.30 | 2850162 | 8.94 | 230853 |
| Observations | 3081015 | | | | | |

Table 2.2: Differences Across Infants Admitted to NICU vs. Not, 2010 NCHS Data

| | Diff | St.D. | Frac. All | N | Frac. NICU | N |
|---|---|---|---|---|---|---|
| Black | -0.053 | 0.001 | 0.141 | 2850162 | 0.194 | 230853 |
| White | 0.049 | 0.001 | 0.773 | 2850162 | 0.724 | 230853 |
| Asian | 0.005 | 0.000 | 0.056 | 2850162 | 0.051 | 230853 |
| Observations | 3081015 | | | | | |

Table 2.3: Racial Differences in NICU Admission Rates

known to have lower birth weight infants at a higher rate and to suffer higher rates of infant mortality. The underlying causal mechanisms are the subject of active research. But as expected here, African-American infants are admitted to the NICU at higher rates than Asian or White infants as is readily visible in Table (2.3). With respect to health status, as expected infants who are admitted to the NICU are in worse health than those who are not. Across all of the conditions in Table (2.4), the fraction of patients having a condition is much higher conditional on NICU admission than it is conditional on non-admission.

Investment in NICU's is restricted in many states by Certificate of Need programs. States with these requirements designate certain hospitals to provide high level services for

| | Diff | Z | St.D. | Frac. All | N | Frac. NICU | N |
|---|---|---|---|---|---|---|---|
| Gest. Diabetes | -0.016 | -90.502 | 0.000 | 0.006 | 2845850 | 0.022 | 229957 |
| Gest. Hyperten. | -0.070 | -158.385 | 0.001 | 0.038 | 2845850 | 0.108 | 229957 |
| Asst. Vent. | -0.227 | -529.406 | 0.001 | 0.024 | 2850162 | 0.251 | 230853 |
| Asst. Vent > 6 hrs. | -0.114 | -543.929 | 0.001 | 0.001 | 2850162 | 0.115 | 230853 |
| Adm. NICU | -1.000 | -1755.282 | 0.000 | 0.000 | 2850162 | 1.000 | 230853 |
| Surfactants | -0.049 | -356.797 | 0.000 | 0.000 | 2850162 | 0.049 | 230853 |
| Antibiotics | -0.204 | -665.038 | 0.001 | 0.005 | 2850162 | 0.209 | 230853 |
| Seizures | -0.003 | -78.811 | 0.000 | 0.000 | 2850162 | 0.003 | 230853 |
| Birth Inj. | -0.001 | -25.557 | 0.000 | 0.001 | 2850162 | 0.002 | 230853 |
| Anencephaly | -0.000 | -10.647 | 0.000 | 0.000 | 2845332 | 0.000 | 227428 |
| Spn. Bif. | -0.002 | -55.179 | 0.000 | 0.000 | 2845332 | 0.002 | 227428 |
| Cy. Cong. Hrt. Dis. | -0.006 | -115.055 | 0.000 | 0.000 | 2845332 | 0.006 | 227428 |
| Diaph. Hern. | -0.001 | -54.052 | 0.000 | 0.000 | 2845332 | 0.001 | 227428 |
| Omphalocele | -0.001 | -41.384 | 0.000 | 0.000 | 2845332 | 0.001 | 227428 |
| Gastroschisis | -0.003 | -92.783 | 0.000 | 0.000 | 2845332 | 0.003 | 227428 |
| Limb Reduction | -0.001 | -22.011 | 0.000 | 0.000 | 2845332 | 0.001 | 227428 |
| Cleft Lip | -0.002 | -34.018 | 0.000 | 0.000 | 2845332 | 0.002 | 227428 |
| Cleft Palate | -0.001 | -32.610 | 0.000 | 0.000 | 2845332 | 0.001 | 227428 |
| Hypospadias | -0.001 | -17.384 | 0.000 | 0.000 | 2845332 | 0.001 | 227428 |
| Observations | 3081015 | | | | | | |

Table 2.4: Differences Across Complicating Conditions

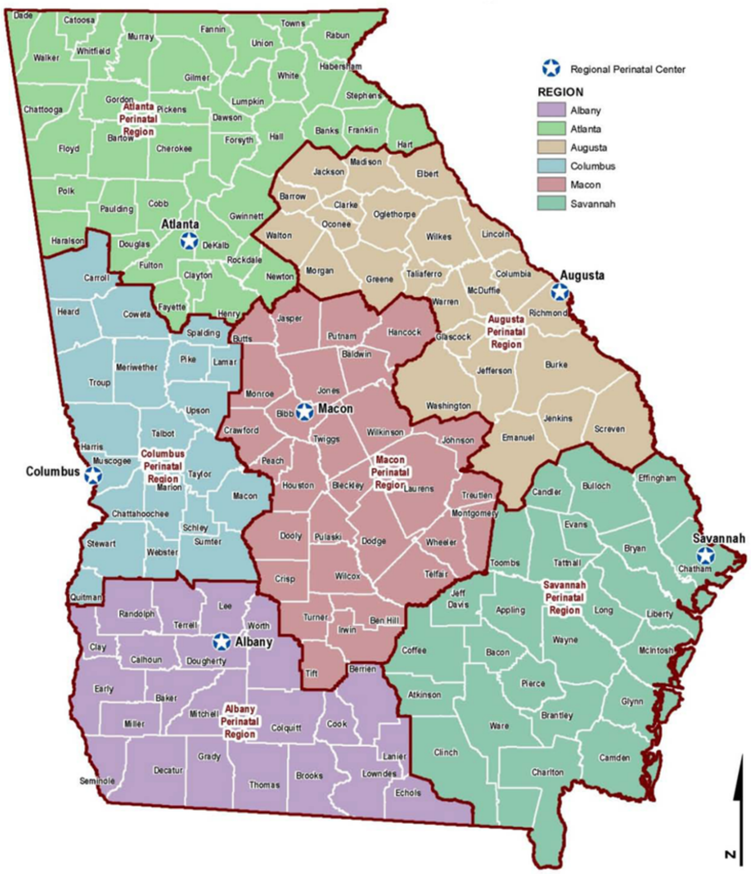



Figure 2.2: Perinatal Regionalization in Georgia

an entire region. The perinatal regionalization system in Georgia is depicted in Figure (2.2). Large blocks of counties are served by designated perinatal care centers, which are responsible for assisting other facilities in the transport of sick neonates. In Georgia's case, each region is served by a single high-level facility. New York and Florida are two other large states with perinatal regionalization systems, though they permit more high level facilities in large cities.

In states without certificate of need control, hospitals have found neonatal intensive

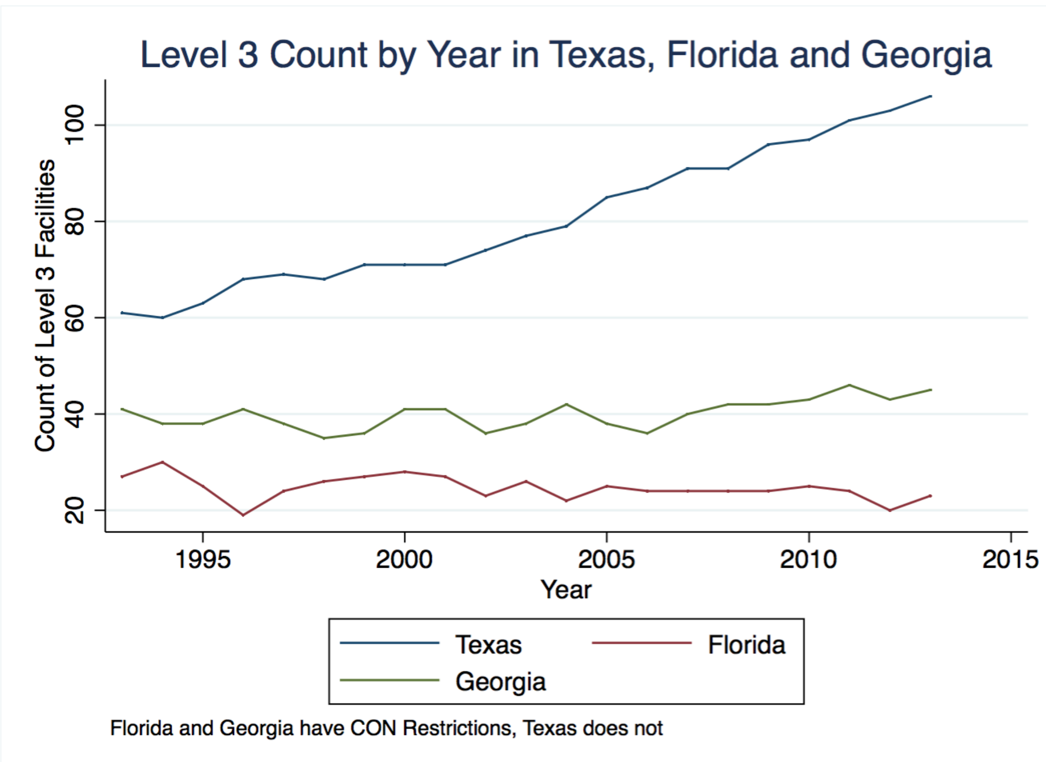



Figure 2.3: Number of Level 3 Facilities

care to be a lucrative investment. In Texas, which is the subject of my paper [15], large urban counties now generally have more Level III units than Level I units. These effects are driven mostly by competitive pressures and business stealing incentives. In CON states, by comparison, rates of observed investment are much, much lower. In Figure (2.3), I plot the number of Level III facilities by year in two states with strong Certificate of Need control (Florida and Georgia) and one state without it (Texas) for 1991 - 2014. As is immediately visible, the number of facilities in CON states does not change much from year to year, while in Texas it grows steadily over the time period of the survey.

The driving force for investment in Texas is the fact that providing this service is very profitable. As I show in [15], adding an intensive care unit results in a substantial increase in general patient volume to the obstetrics ward. Profit increases can come via two channels: first, the ability to provide new, expensive services to a sick population, second, an increase in patient volume from those who are not in need, but who choose to visit a hospital out of a precautionary motive related to the possibility that they might need the service. Observed investment behavior in Texas in Figure (2.3) suggests that it is very unlikely that hospitals are losing substantial sums on investing in this service. If anything, Figure (2.3) is understating the attractiveness of the investment and the competitive pressures hospitals are subject to. Most of the new Level 3 units constructed in the state between 1990 and 2012 are built in urban areas which are already well-served by NICUs. Access does not expand spatially. More details are available in [15].

## 2.4 Data

The data consist of the universe of infants admitted to neonatal intensive care units in Texas at birth, plus all of those who were low birth weight (2500 g) or less, plus all neonatal deaths (28 days or fewer). The data cover 381 unique facilities and eight years. Over the whole period of the data, the characteristics of the population are relatively stable. There are between 43,000 - 46,000 patients in the three groups per year. Nearly all (more than 99%) are born in hospitals. They tend to be premature - mean estimated weeks of gestation is around 35 (see Table (2.2) for a comparison to those not admitted to a NICU at birth). One characteristic which does change over time is the insurance status of the population, where "self-pay" declines and "Medicaid" increases Summary statistics concerning the data are in Table 2.5.

Data for the whole population of newborns in Texas is available for 2005 - 2010 using data from the National Center for Health Statistics. This data includes information on the complete universe of births in Texas every year. It also includes additional information about each patient in the state who died within one year. Summary measures are in Table (2.6). The comparisons in Tables (2.2), (2.3) and (2.4) are all made using this data. The national data includes more covariates and much more detailed information than are available in the Texas birth certificate data, but that dataset does not include any information about the hospital of birth, which is crucial to determining the level and volume of patients treated at the NICU.

For some of the entries in Table (2.6), I use the Texas Department of State Health Statistics (DSHS) Inpatient Public Use Data File. These files contain information on the universe of discharges from all hospitals in the state annually, except a small number which either very small counties or which provide specialized services. The latter category includes specialty children's hospitals, which is an important data limitation, as these children's hospitals are present in the birth certificate data. The largest metro areas in the state each have at least one specialty children's hospital. To compute patient distances to their chosen hospitals, I use information on the mother's zip code of residence at the time of birth. (This is available for more than 90% of all births in the inpatient data file.) I measure distances from the center of the zip code to the location of the hospital and report in Table (2.6) the distribution of distances traveled.

The other source of data which I use is the Texas Department of State Health Services Annual Survey of Hospitals ([104]). This survey provides a complete picture of hospitals in the state. As with the Inpatient Public Use Data File, all but a very small number of facilities in small counties, plus a small group of specialty hospitals, are required to complete the survey every year. The survey is jointly administered with the better-known American Hospital Association's Annual Survey, which is a standard source of data widely used in nearly all papers in this literature. The survey contains a wide range of variables covering inpatient utilization, the existence of different services and facilities, plus some measures of staffing and financial information. For this paper, I use DSHS's survey for 2005-2012 to track which hospitals in the data have Level 1, level 2, or level 3 NICU's. The survey permits me to observe entry, exit and level changes over time.

The patients admitted to NICU's resemble the whole population on most dimensions. As is to be expected given that prematurity is one of the leading causes of low birth weight, there estimated gestational age is lower than that in the whole population by about three weeks and the standard deviation in estimated gestational age is about double that in the

| Characteristic | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|---|---|---|
| Patients | 43082 | 45338 | 46039 | 47132 | 48039 | 46647 | 45660 | 46400 |
| Mortality Rate (/1000) | 33.5 | 32.4 | 31.0 | 30.2 | 28.5 | 29.7 | 28.5 | 28.4 |
| Percent Born in Hospital | 99.7 | 99.6 | 99.6 | 99.6 | 99.6 | 99.5 | 99.6 | 99.6 |
| Unique Hospitals | 273 | 275 | 267 | 271 | 276 | 262 | 264 | 261 |
| Fraction Male | 0.508 | 0.506 | 0.505 | 0.510 | 0.509 | 0.508 | 0.510 | 0.510 |
| Estimated Weeks Gestation | 35.1 | 35.1 | 35.1 | 35.2 | 35.2 | 35.2 | 35.2 | 35.2 |
| (S.D.) | (4.5) | (4.4) | (4.5) | (4.4) | (4.2) | (4.2) | (4.2) | (4.2) |
| Birth Weight (grams) | 2312 | 2313 | 2309 | 2328 | 2343 | 2369 | 2372 | 2390 |
| (S.D.) | (779) | (783) | (776) | (773) | (781) | (788) | (795) | (820) |
| Transferred (%) | 7.5 | 6.8 | 6.9 | 6.2 | 6.2 | 6.0 | 6.4 | 5.2 |
| Distances Traveled | | | | | | | | |
| Average Distance Traveled | 12.8 | 12.5 | 12.6 | 12.6 | 12.5 | 12.6 | 12.7 | 12.7 |
| (S.D.) | (14.6) | (14.1) | (14.1) | (14.3) | (13.8) | (14.1) | (14.5) | (14.4) |
| Distance 5th Percentile | 1.6 | 1.6 | 1.6 | 1.6 | 1.7 | 1.7 | 1.6 | 1.6 |
| Distance 95th Percentile | 38.1 | 36.8 | 36.7 | 37.6 | 37.0 | 36.8 | 37.7 | 37.7 |
| Insurance Status | | | | | | | | |
| Medicaid | 43.6 | 43.7 | 43.8 | 46.8 | 49.2 | 50.2 | 50.4 | 48.8 |
| Private | 37.6 | 35.9 | 36.6 | 36.8 | 35.7 | 35.4 | 35.8 | 36.0 |
| Self-pay | 13.9 | 16.9 | 14.4 | 10.7 | 9.0 | 8.3 | 7.3 | 7.5 |
| Other/Unknown | 4.8 | 3.51 | 5.2 | 5.75 | 6.1 | 6.2 | 6.5 | 7.7 |

Table 2.5: NICU Admit Sample Characteristics

whole population. The patients in the NICU admissions sample have a much higher mortality rate, which again is to be expected.

## 2.5 Estimation

### 2.5.1 Probit Estimation of Mortality

I estimate a mortality probit equation as a function of lagged hospital volume. The outcome $y_i^*$ is 1 if patient $i$ is recorded to have died. I consider only patients in the data who

| Characteristic | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|
| Patients | 392,222 | 405,879 | 414,170 | 412,147 | 408,391 | 392,764 |
| Mortality Rate (/1000) | 6.13 | 5.96 | 5.9 | 5.8 | 5.8 | 5.7 |
| Percent Born in Hospital | 98.7 | 98.7 | 98.7 | 98.7 | 98.7 | 98.7 |
| Unique Hospitals | 290 | 289 | 287 | 286 | 276 | 285 |
| Fraction Male | 0.512 | 0.511 | 0.511 | 0.512 | 0.510 | 0.510 |
| Estimated Weeks Gestation | 38.1 | 38.3 | 38.3 | 38.3 | 38.2 | 38.3 |
| (S.D.) | (2.1) | (2.1) | (2.1) | (2.2) | (2.1) | (2.1) |
| Birth Weight (grams) | 3244 | 3235 | 3232 | 3227 | 3223 | 3226 |
| (S.D.) | (585) | (587) | (581) | (582) | (582) | (578) |
| Percent LBW | 8.3 | 8.4 | 8.3 | 8.4 | 8.5 | 8.4 |
| Percent VLBW | 1.4 | 1.5 | 1.5 | 1.4 | 1.5 | 1.4 |
| Distances Traveled | | | | | | |
| Average Distance Traveled | 10.9 | 10.9 | 10.9 | 11.0 | 11.0 | 11.0 |
| (S.D.) | (11.7) | (11.5) | (11.5) | (11.7) | (11.7) | (11.7) |
| Distance 5th Percentile | 0.83 | 0.81 | 0.82 | 0.83 | 0.82 | 0.82 |
| Distance 95th Percentile | 31.3 | 31.3 | 31.1 | 31.5 | 31.5 | 31.4 |
| Insurance Status | | | | | | |
| Medicaid | 43.6 | 43.7 | 43.8 | 46.8 | 49.2 | 50.2 |
| Private | 37.6 | 35.9 | 36.6 | 36.8 | 35.7 | 35.4 |
| Self-pay | 13.9 | 16.9 | 14.4 | 10.7 | 9.0 | 8.3 |
| Other/Unknown | 4.8 | 3.51 | 5.2 | 5.75 | 6.1 | 6.2 |

Table 2.6: All Texas Births - Population Characteristics, 2005 - 2010

are admitted to the NICU.

$$y_i^* = \alpha + \beta X_i + \gamma v_h + \sum_w \psi_w + \sum_t \phi_t + \sum_s \pi_s + \delta 1_{wt<1500g.} + \epsilon_i \quad (2.1)$$

$$y_i = 1_{y_i^*>0} \quad (2.2)$$

The parameter of interest is $\gamma$ on the lagged patient volume measure $v_h$. Across different specifications I control for individual health states $X_i$, gestational age $\psi_w$ (closely correlated with birth weight), year fixed effects $\phi_t$, patient insurance status $\pi_s$, and a lagged hospital-specific volume term $v_h$ recording NICU admits for the prior quarter. I include an indicator for whether the patient is very low birth weight.

One concern with the previous model is that hospital volume is likely endogenous to an underlying and unobserved quality parameter. The choice of hospital is best thought of as the joint choice of patients and their doctors, a point made in [62]. Patients (and especially their doctors) know more about the differences among hospitals in any market than the econometrician does. They are therefore likely to endogenously refer patients to unobservably better hospitals. This means that hospital volume is correlated with the error term $\epsilon_i$ in Equation (2.1).

If doctors know more about hospitals and the variations in quality among them than the econometrician, they would likely arrange for sicker patients to be admitted to higher quality hospitals where they will receive better care. What is worth noting is that this selective referral pattern likely biases us against finding any positive effect of volume on the quality of outcome. Specifically, unobservably higher quality facilities are being sent sicker

| | (1) 2005 | (2) 2006 | (3) 2007 | (4) 2008 | (5) 2009 | (6) 2010 |
|---|---|---|---|---|---|---|
| Distance to Chosen | -.1350956 | -.1401679 | -.1386198 | -.1383008 | -.1372531 | -.1378965 |
| | .0007721 | .0007772 | .0007738 | .0007489 | .0007386 | .0007476 |
| Distance Squared | .0003868 | .0003983 | .0003936 | .000397 | .0003966 | .0003985 |
| | 2.92e-06 | 2.92e-06 | 2.95e-06 | 2.83e-06 | 2.89e-06 | 2.89e-06 |
| Level 3 | 1.076136 | 1.115735 | 1.053772 | 1.34836 | 1.297681 | 1.146061 |
| | .0190674 | .019926 | .0202007 | .0224778 | .0228856 | .0227744 |
| Level 2 | .1565831 | .2360021 | .1646441 | .3788195 | .4394275 | .2950157 |
| | .0259654 | .0261861 | .02492 | .0253428 | .0279101 | .0285319 |
| Obstetrics Level 1 | 1.950811 | 2.075353 | 1.795612 | 2.075757 | 1.803341 | 2.047937 |
| | .0325649 | .0321277 | .0309018 | .030969 | .0303161 | .032197 |
| Obstetrics Level 2 | 2.452112 | 2.512113 | 2.369475 | 2.2748 | 2.116337 | 2.373674 |
| | .0329725 | .0326112 | .0310458 | .0322187 | .0311317 | .0334697 |
| Obstetrics Level 3 | 3.172436 | 3.185297 | 3.096666 | 2.793922 | 2.728546 | 2.96591 |
| | .034387 | .0343069 | .0325804 | .0335424 | .0326682 | .0349757 |
| N | 43,960 | 46,372 | 46,952 | 47,997 | 48,986 | 47,395 |

Table 2.7: Estimated Choice Models by Year

patients. Their patient volumes increase, but this same population of patients has a higher probability of mortality than normal. The hospital-specific mortality rate will be lower, since the composition of patients is sicker than the population average. That is, the most obvious selection-into-facilities story suggests that we should find no effect, or that the true effects is likely to be larger than the naively measured version here. At the same time, the effect on unobservably worse facilities runs in the opposite direction: as doctors send sick patients away from lower-quality facilities, the average mortality risk of patients who remain is better (they are at lower risk of dying) and the volume at the facility is lower.

### 2.5.2 Instrumenting for Volume

To solve this problem, I instrument for hospital volume $v$, following a procedure due to [54], [44] and [45]. These authors estimate patient choice models for hospital features as a function of observable features of the hospital, features of the patient (e.g., patient demographics), and features of the hospital-patient pair (e.g., distance). Using this model, I predict patient choice probabilities and aggregate them across all of the patients in the data to generate expected hospital patient shares. Hospitals which serve densely populated areas or which offer more desirable services (e.g., higher level facilities) will have a higher expected volume than those which lack these features. Hospital level fixed effects are not included, since these would include unobserved hospital-specific quality. This model captures only those features which are observable and do not depend on unobserved hospital quality. The predicted volume measure, therefore, is a function only of observable characteristics of patients and hospitals, not the underlying unobserved quality measure.

I do not constrain patient choices by existing market definitions, whether within a county, or within state Public Health Regions (groups of 10-15 counties). I permit each patient to have a very wide range of possible choices: I permit choice among the 50 closest hospitals in the state. This permits a very wide range of choices. Very few patients choose hospitals which are that distant from their homes. In the average quarter, I observe fewer than 50 patients out of 85,000 choosing the 50-th hospital. In fact, fewer than 50 patients choose any hospital between 45 - 50th closest. This is in part because these facilities are generally quite far away: the 50th closest hospital is on average about 60 miles from a patient's zip code of residence, with a large standard deviation (40 miles).

Actual hospital volume is correlated with this expected volume measure $\hat{v}$, but predicted hospital volume $\hat{v}$ does not otherwise enter into the mortality equation except via $v$. Expected hospital volume is then correlated with actual hospital volume, but does not directly enter into Equation (2.1). Furthermore, this volume measure is not a function of unobserved hospital quality, because it is estimated as a function of hospital, patient and patient-hospital observables only. With this in mind, I instrument for realized volume using the predicted volume measure in Equation (2.4)

$$
\begin{aligned}
y^*_{i,h,t} &= \alpha + \beta X_i + \gamma v_h + \sum_w \psi_w + \sum_t \phi_t + \sum_s \pi_s + \delta 1_{wt<1500g.} + \epsilon_i && (2.3)\\
v_h &= \alpha' + \beta' X_i + \sum_w \psi'_w + \sum_t \phi'_t + \sum_s \pi'_s + \gamma' \hat{v}_h + \epsilon'_i && (2.4)\\
y_i &= 1_{y^*_i>0} && (2.5)
\end{aligned}
$$

Much of the variation in this instrument is driven by entry and exit among other facilities. As other facilities enter, exit or change levels, the predicted volume will change as existing facilities become relatively more or less attractive. I observe 54 changes in level during over the time frame covered by the data representing 23 unique counties. This understates the number of facilities exposed to a level change by a competitor, however. The total number of hospitals across those 23 counties (not counting neighboring counties which may plausibly considered to be in the same market) is 110, out of a total of about 350, so the number who are potentially facing a demand shock due to the upgrade or downgrade of a competitor is large as a fraction of the total. But this should be considered a lower bound on the total, as most counties in Texas are quite small in area and most hospitals are concentrated around the large urban areas.

| | (1) No IV | (2) Vol. IV | (3) Vol. IV | (4) Vol. IV | (5) Vol. IV |
|---|---|---|---|---|---|
| Prev. Q. Vol. | -0.0004*** | -0.0002 | -0.0002* | -0.0002* | -0.0002* |
| | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| Medicaid | | | 0.0000 | 0.0000 | 0.0000 |
| | | | . | . | . |
| Private Insurance | | | -0.0746*** | -0.0761*** | -0.0764*** |
| | | | 0.0168 | 0.0169 | 0.0173 |
| Self-pay | | | 0.2109*** | 0.2171*** | 0.2185*** |
| | | | 0.0226 | 0.0226 | 0.0234 |
| Other | | | 0.1581*** | 0.1593*** | 0.1450*** |
| | | | 0.0359 | 0.0360 | 0.0374 |
| Unknown | | | 0.1709 | 0.1794 | 0.1991 |
| | | | 0.1189 | 0.1190 | 0.1220 |
| VLBW=0 | | | | 0.0000 | 0.0000 |
| | | | | . | . |
| VLBW=1 | | | | 0.3829*** | 0.3648*** |
| | | | | 0.0310 | 0.0317 |
| Assisted Ventilation Immediately Following Delivery | | | | | 0.1581*** |
| | | | | | 0.0171 |
| Surfactant Replacement Therapy | | | | | 0.1252*** |
| | | | | | 0.0302 |
| Antibiotics for Suspected Neonatal Sepsis | | | | | -0.1381*** |
| | | | | | 0.0225 |
| Seizure or Serious Neurologic Dysfunction | | | | | 0.9756*** |
| | | | | | 0.0789 |
| Significant Birth Injury | | | | | 0.5052*** |
| | | | | | 0.1247 |
| Anencephaly | | | | | 2.5848*** |
| | | | | | 0.1285 |
| Meningomyelocele/Spina Bifida | | | | | 0.3118* |
| | | | | | 0.1590 |
| Cyanotic Congenital Heart Disease | | | | | 1.1402*** |
| | | | | | 0.0680 |
| Congenital Diaphragmatic Hernia | | | | | 1.6850*** |
| | | | | | 0.1025 |
| Omphalocele | | | | | 1.2637*** |
| | | | | | 0.1507 |
| Gastroschisis | | | | | 0.3786*** |
| | | | | | 0.1078 |
| Limb Reduction Defect | | | | | 1.0958*** |
| | | | | | 0.1351 |
| Hypospadias | | | | | 0.4376** |
| | | | | | 0.1519 |
| Constant | -1.6149*** | -1.6286*** | -1.6845*** | -1.8265*** | -1.8925*** |
| | 0.2686 | 0.2686 | 0.2691 | 0.2745 | 0.2775 |
| Expected Volume | | 0.3163*** | 0.3112*** | 0.3112*** | 0.3079*** |
| | | 0.0008 | 0.0008 | 0.0008 | 0.0008 |
| Medicaid | | | 0.0000 | 0.0000 | 0.0000 |
| | | | . | . | . |
| Private Insurance | | | 28.3752*** | 28.3765*** | 28.0481*** |
| | | | 0.4444 | 0.4444 | 0.4371 |
| Self-pay | | | 17.7340*** | 17.7211*** | 17.4811*** |
| | | | 0.7250 | 0.7251 | 0.7139 |
| Other | | | -9.8589*** | -9.8645*** | -7.9603*** |
| | | | 1.1523 | 1.1523 | 1.1300 |
| Unknown | | | -39.9538*** | -39.9761*** | -45.2729*** |
| | | | 3.9631 | 3.9631 | 3.8884 |
| VLBW=0 | | | | 0.0000 | 0.0000 |
| | | | | . | . |
| VLBW=1 | | | | -1.4665 | -3.1030** |
| | | | | 1.0153 | 0.9959 |
| Assisted Ventilation Immediately Following Delivery | | | | | 35.2196*** |
| | | | | | 0.4684 |
| Surfactant Replacement Therapy | | | | | 9.0547*** |
| | | | | | 1.0995 |
| Antibiotics for Suspected Neonatal Sepsis | | | | | 11.9608*** |
| | | | | | 0.5707 |
| Seizure or Serious Neurologic Dysfunction | | | | | -3.8932 |
| | | | | | 4.0034 |
| Significant Birth Injury | | | | | -14.0082* |
| | | | | | 5.5829 |
| Anencephaly | | | | | -0.1737 |
| | | | | | 8.4286 |
| Meningomyelocele/Spina Bifida | | | | | -18.2393*** |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | 5.3480 |
| Cyanotic Congenital Heart Disease | | | | | -8.7594* |
| | | | | | 3.5526 |
| Congenital Diaphragmatic Hernia | | | | | -3.2879 |
| | | | | | 6.5629 |
| Omphalocele | | | | | -6.7516 |
| | | | | | 8.7698 |
| Gastroschisis | | | | | 1.5087 |
| | | | | | 3.5998 |
| Limb Reduction Defect | | | | | -8.1513 |
| | | | | | 7.3173 |
| Hypospadias | | | | | -4.5515 |
| | | | | | 5.9899 |
| Constant | | -54.3654*** | -60.5406*** | -60.1214*** | -75.2565*** |
| | | 11.0475 | 10.9134 | 10.9172 | 10.7047 |
| athrho2_1 | | -0.0474*** | -0.0421*** | -0.0403*** | -0.0552*** |
| | | 0.0103 | 0.0103 | 0.0104 | 0.0107 |
| lnsigma2 | | 4.4949*** | 4.4824*** | 4.4824*** | 4.4625*** |
| | | 0.0016 | 0.0016 | 0.0016 | 0.0016 |
| IV | No | Yes | Yes | Yes | Yes |
| Insurance | No | No | Yes | Yes | Yes |
| VLBW | No | No | No | Yes | Yes |
| HealthStates | No | No | No | No | Yes |
| ExogeneityPval | | 3.72e-06 | .0000476 | .0001017 | 2.35e-07 |
| N | 186611 | 186611 | 186611 | 186611 | 186611 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

The key coefficient on volume in the previous quarter maintains the expected sign across specifications, both with and without the IV for volume. The effect is negative and significant. Furthermore, a Hausman test rejects the exogeneity of volume. The partial effects are plotted in Figure (2.1). The key points to notice are: that mortality probability is declining with the admissions in the prior quarter, that there is some limited evidence to support a selective referral story, and that the confidence intervals around the point estimates exclude any straight-line, constant mortality rate as a function of volume. The selective referral story is compatible with that outlined at the beginning of the paper: it appears that correcting for the endogeneity of volume does show that lower volume facilities have unobservably healthier patients, while high volume patients have unobservably sicker patients. This is consistent with a story in which doctors refer patients from low volume facilities where care is unobservably worse, perhaps due to less learning by doing, to better quality, higher volume facilities where it is better. The estimated effects are not consistent with a story in which volume does not matter to the production of quality.

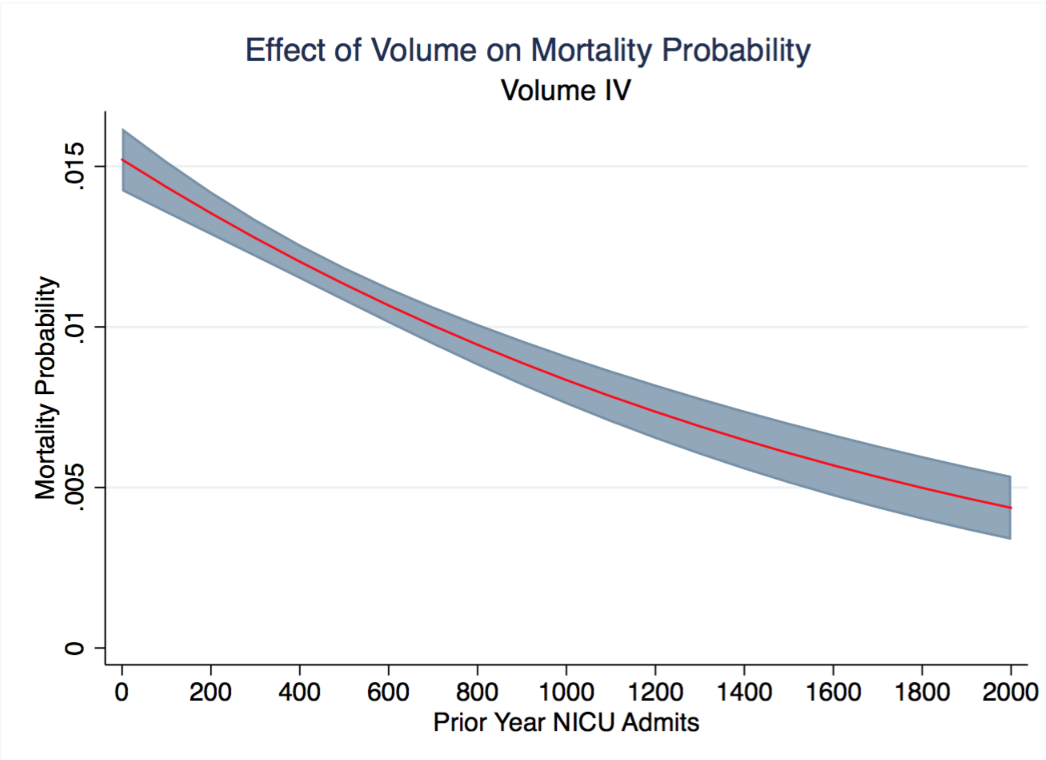



Figure 2.4: Effects of Annual Volume on Mortality Probability

The graph of the partial effects of volume on outcome are shown with confidence intervals again in Figure (2.4). The figure shows the effects of volume on mortality probability as annual volume is varied from the 5th - 95h percentile of observed values. This estimation includes the IV for volume and includes hospital specific fixed-effects. The key point point to take from the estimated partial effects and confidence intervals is that all straight lines are excluded. A constant effect of patient volume on mortality is not consistent with the data. While this estimation uses NICU admits in the prior year, a very similar graph would result if the estimation were re-run using the volume of NICU patients in the prior quarter, prior month, or several prior months.

Furthermore, the effects are large. A reduction of 1% in mortality probability from moving to the lowest to highest volume facilities is significant. I show the results of transferring all patients in the state from low volume to high volume facilities in Figure (2.5). The total potential savings in lives over the entire state is nearly 150 infants annually.

## 2.6 Learning and Forgetting

The most plausible explanation for the effects of volume on outcome is that some learning occurs at the level of the facility. Learning in the context of medical care has been the subject of many papers, among then [64], [35], [54], [44] and [45]. The mechanism in this context should be thought of as learning happening at the team level for several reasons. First of all, average durations of stay in the NICU are long: about 13.2 days on average. Patients are cared for over an extended period of time by a team of people. NICU's are supervised by neonatologists per state requirements, but most hour-to-hour management is done by nurses. Unfortunately, no data is available about specific staff members present in at any hospital. Informally, however, the mechanism at work should be thought of as one where doctors and nurses get better at treating patients through practice. As time passes and more patients pass through the NICU, staff improve their ability to predict what will work to help each individual patient.

The following two short tables show the effects of lagged monthly and lagged quarterly volume on the mortality probability for admits to Level III facilities. The lagged monthly effect is more strongly negative than the lagged quarterly effect. In Table (2.10) I instrument for monthly volume and in Table (2.9) for quarterly volume and include hospital fixed effects. Due to the inclusion of the fixed effect, identification here comes from variation in hospital-

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | No IV | Vol. IV | Vol. IV | Vol. IV | Vol. IV |
| Prev. Q. Vol. | -0.0004*** | -0.0002 | -0.0002* | -0.0002* | -0.0002* |
| | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| IV | No | Yes | Yes | Yes | Yes |
| Ins. | No | No | Yes | Yes | Yes |
| VLBW | No | No | No | Yes | Yes |
| Health States | No | No | No | No | Yes |
| Hausman Test | | 3.31e-06 | .0000426 | .0000902 | 2.42e-07 |
| N | 185817 | 185817 | 185817 | 185817 | 185817 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.9: Prior Quarter Volume Effect on Mortality Probability

specific volume.

Including 12 lagged months both with and without facility fixed effects paints a similar picture and suggests that there is an important role for forgetting in modeling the underlying effects at work in this environment. In both Table (2.11) and Table (2.12), the most recent lagged month has the strongest negative effect on the mortality rate. Even the second lagged month, while still of the correct sign, is not statistically distinguishable from zero. Later months have even wider confidence intervals and all include zero. The fact that the most recent months matter and those in the more distant past do not suggests that forgetting plays a significant role in the process.

The estimate coefficients all suggest that patient volume matters, but the month-specific coefficients provide support to the idea that it is recent volume which matters more than volume in the distant past. This suggests an important role for forgetting in this market.

To examine these effects more carefully, I estimate two models of forgetting, one of

| | (1) Neonatal Death | (2) Neonatal Death | (3) Neonatal Death |
|---|---|---|---|
| Admits Pr. Month | -0.0088* | -0.0066 | -0.0077 |
| | 0.0044 | 0.0043 | 0.0044 |
| IV | Yes | Yes | Yes |
| Ins. | Yes | Yes | No |
| FEs | Yes | Yes | Yes |
| Time | Mn. | Mn. | Mn. |
| Health States | Yes | No | Yes |
| N | 188445 | 188445 | 188445 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 2.10: Prior Month Volume Effect on Mortality Probability

which is similar to that estimated by [17] in his paper on forgetting in the production of airlines.

### 2.6.1 Organizational Forgetting

To assess the depreciation rate of knowledge at the firm level, I estimate two nonlinear models of the effects of lagged volume on the mortality outcome. In the first model, I assume a strict geometric depreciation rate for lagged experience at the facility level. Past facility experience is denoted $V_i$ and is discounted by $\delta \in (0, 1)$. This regression includes patient-specific health states (the same used in earlier specifications), hospital facility information and a set of year dummies. (This model does not include hospital-specific fixed effects.) The coefficient of interest is the $\delta_1$ which multiplies lagged hospital-specific experience. I include 12 lagged months of experience.

| | (1) Neonatal Death | (2) Neonatal Death | (3) Neonatal Death | (4) Neonatal Death | (5) Neonatal Death |
|---|---|---|---|---|---|
| Lag 1 Months NICU Admits | -0.0025** | -0.0025** | -0.0026** | -0.0026** | -0.0025** |
| | 0.0009 | 0.0009 | 0.0010 | 0.0010 | 0.0010 |
| Lag 2 Months NICU Admits | -0.0007 | -0.0007 | -0.0008 | -0.0008 | -0.0010 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 3 Months NICU Admits | 0.0007 | 0.0007 | 0.0007 | 0.0007 | 0.0011 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 4 Months NICU Admits | 0.0011 | 0.0011 | 0.0011 | 0.0010 | 0.0012 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 5 Months NICU Admits | 0.0008 | 0.0008 | 0.0008 | 0.0009 | 0.0008 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 6 Months NICU Admits | -0.0012 | -0.0012 | -0.0012 | -0.0012 | -0.0011 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 7 Months NICU Admits | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 0.0001 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 8 Months NICU Admits | 0.0008 | 0.0008 | 0.0008 | 0.0008 | 0.0006 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 9 Months NICU Admits | -0.0013 | -0.0013 | -0.0013 | -0.0012 | -0.0012 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0011 |
| Lag 10 Months NICU Admits | 0.0009 | 0.0009 | 0.0009 | 0.0008 | 0.0009 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 11 Months NICU Admits | -0.0009 | -0.0009 | -0.0009 | -0.0008 | -0.0008 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 12 Months NICU Admits | 0.0003 | 0.0003 | 0.0004 | 0.0005 | 0.0003 |
| | 0.0009 | 0.0009 | 0.0009 | 0.0009 | 0.0009 |
| IV | No | No | No | No | No |
| Ins. | No | No | Yes | Yes | Yes |
| VLBW | No | No | No | Yes | Yes |
| Health States | No | No | No | No | Yes |
| FEs | Yes | Yes | Yes | Yes | Yes |
| N | 164660 | 164660 | 164660 | 164660 | 164660 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.11: 12 Prior Months Volume Effect on Mortality Probability with Hospital FEs

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Neonatal Death | Neonatal Death | Neonatal Death | Neonatal Death | Neonatal Death |
| Lag 1 Months NICU Admits | -0.0020* | -0.0020* | -0.0023* | -0.0023* | -0.0022* |
| | 0.0009 | 0.0009 | 0.0009 | 0.0009 | 0.0009 |
| Lag 2 Months NICU Admits | -0.0009 | -0.0009 | -0.0010 | -0.0011 | -0.0013 |
| | 0.0009 | 0.0009 | 0.0009 | 0.0009 | 0.0010 |
| Lag 3 Months NICU Admits | 0.0009 | 0.0009 | 0.0008 | 0.0008 | 0.0011 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 4 Months NICU Admits | 0.0009 | 0.0009 | 0.0009 | 0.0009 | 0.0010 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 5 Months NICU Admits | 0.0009 | 0.0009 | 0.0009 | 0.0009 | 0.0009 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 6 Months NICU Admits | -0.0009 | -0.0009 | -0.0010 | -0.0010 | -0.0010 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 7 Months NICU Admits | 0.0006 | 0.0006 | 0.0004 | 0.0005 | 0.0004 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 8 Months NICU Admits | 0.0010 | 0.0010 | 0.0009 | 0.0009 | 0.0007 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 9 Months NICU Admits | -0.0011 | -0.0011 | -0.0012 | -0.0011 | -0.0011 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 10 Months NICU Admits | 0.0004 | 0.0004 | 0.0006 | 0.0004 | 0.0005 |
| | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| Lag 11 Months NICU Admits | -0.0010 | -0.0010 | -0.0009 | -0.0008 | -0.0008 |
| | 0.0009 | 0.0009 | 0.0010 | 0.0010 | 0.0010 |
| Lag 12 Months NICU Admits | -0.0001 | -0.0001 | 0.0003 | 0.0003 | 0.0001 |
| | 0.0009 | 0.0009 | 0.0009 | 0.0009 | 0.0009 |
| IV | No | No | No | No | No |
| Ins. | No | No | Yes | Yes | Yes |
| VLBW | No | No | No | Yes | Yes |
| Health States | No | No | No | No | Yes |
| N | 165845 | 165845 | 165845 | 165845 | 165845 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.12: 12 Month Volume Effect on Mortality Probability

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\delta_1$ | 0.5370 | 0.5367 | 0.5367 | 0.5367 | 0.5367 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Health States | N | N | Y | Y | Y |
| Hospital Chars. | N | Y | N | Y | Y |
| Ins. Stat. | N | Y | Y | N | Y |
| Year | Y | Y | Y | Y | Y |

Table 2.13: Estimated Depreciation Rates

$$Mortality_i = \beta_0 + \sum_{i=0}^{N} \delta_1^{N-i} V_i + \Gamma X_i + \Phi X_h + \Psi \Omega_t + \epsilon \qquad (2.6)$$

The estimated monthly depreciation rate in this model is extremely high: about 50% of the stock of experience present at the beginning of the month has vanished by the end of the month. Of the experience present at the beginning of a year, only 0.04% is present at the end of the year. This holds across the several specifications. This estimate, while much higher than that of [17] or [108], is lower than that in [33], who estimate forgetting rates in pizza franchises.

The second specification I estimate treats all accumulated experience $E_t$ differently from contemporaneous experience. This is the specification of [17] and other papers in the literature, include [33]. In Benkard's case, however, the estimated monthly depreciation rates are much lower than those I estimate here. These rates are on the higher end of what has been estimated in this literature. The model I estimate is follows:

$$Mortality_i = \beta_0 + \alpha \log(\delta_2 E_{t-1} + v_{t-1}) + \Gamma X_i + \Phi X_h + \Psi \Omega_t + \epsilon$$

Cumulative experience is here defined as:

$$E_t = \delta_2 E_{t-1} + v_t$$

This cumulative experience measure should be thought of as a reduced form for the effect of prior experience (also the interpretation in [17]) . There are important data limitations which prevent drawing stronger conclusions about the exact form of forgetting in this context. As previously mentioned, patients will be treated over the course of their stays by several nurses and the nurses will potentially be supervised by more than one doctor. Nurse to patient ratios are generally quite low: perhaps one nurse to two or three patients, but patients are monitored around the clock, so it is certain that they will be monitored by more than one nurse over the course of a day. Given that the average duration of a stay is nearly two weeks, it is also certain that a given patient will cycle through several providers. The data is not informative about who is actually looking after which patients on any given day, nor which doctors are present at the facility.

Therefore, while it is quite plausible given the institutional details to assume that learning happens at the level of the team, delving more deeply into how that process actually works is not possible. There are potentially several processes which could be at work: individual nurses may learn, but since they are responsible for small numbers of patients perhaps the variety of cases they see is small. Doctors and nurses may better coordinate care given time and experience. Nurses may become more effective at sharing information across shifts. Several different possibilities can be contemplated.

Furthermore, attrition is potentially an important problem in this environment. The

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\delta_2$ | 0.091 | 0.049 | 0.057 | 0.067 |
| | (0.26) | (0.142) | (0.15) | (0.2) |
| Health States | N | N | Y | Y |
| Hospital Chars. | N | Y | N | Y |
| Ins. Stat. | N | Y | Y | N |
| Year | Y | Y | Y | Y |

Table 2.14: Estimated Depreciation Rates

rate at which nursing staff turns over is high. This is an issue which hospitals track and care about since the costs of training new nursing staff are significant. When a nurse separates from employment at a given hospital, the knowledge he has accumulated disappears with him. Since separation rates are high but unobserved, this causes an overestimate of the actual underlying rate of forgetting. On this issue in a different health care context, see [35]. However, the underlying forgetting rate within an individual doctor or nurse, though of independent interest, is not the relevant quantity here. If nurses separate from employment in NICU's and take their accumulated experience, and this raises the probability of mortality within a facility, that is the relevant quantity for the purposes of this estimation and the counterfactuals. Provided rates of nursing separation are similar across facilities and not correlated with some other underlying unobservable related to mortality, this estimation should be the relevant quantity.

The estimated forgetting rate in the second model is quite high, but the confidence intervals are large enough to include zero in each specification. Again I include individual-specific health states, hospital characteristics, a time trend and a constant. It is impossible to rule out full depreciation after one month with this model. That would be broadly consistent with what I find above using the 12 separate lagged months in the probit model, with or without hospital-specific fixed effects: the most recent month matters, while months earlier do not seem to have a significant negative effect on mortality. It is also broadly consistent with the first model of depreciation in Equation (2.6). Whether estimated as a probit with separate month lags or with two separate non-linear models of depreciation, the estimated forgetting rate is quite high.

## 2.7 Implications

The results from the probit estimation of volume on mortality suggest that substantial savings in lives can be realized by transferring patients from the lowest volume to the highest volume facilities in their market. Valuing each life saved at $7,000,000 suggests sizable gains due to centralization.

I conduct the following experiment, the results of which are in Figure (2.5). For each county in the state, I transfer all of the patients admitted to the NICU in the county to the hospital with the highest NICU volume. I compute the mortality rate implied by that volume of patients and then compute an expected mortality rate under the assumption of centralization. I also compute the expected mortality rates implied by actual patient volumes at the separate facilities to which patients were actually admitted. I plot the difference between the expected patient deaths in the current market equilibrium vs. those in the centralized market in Figure (2.5). The x-axis shows lives saved per county for the 20 or so counties with populations over 250,000.

As is immediately visible from the graph, the savings in lives over the entire state are

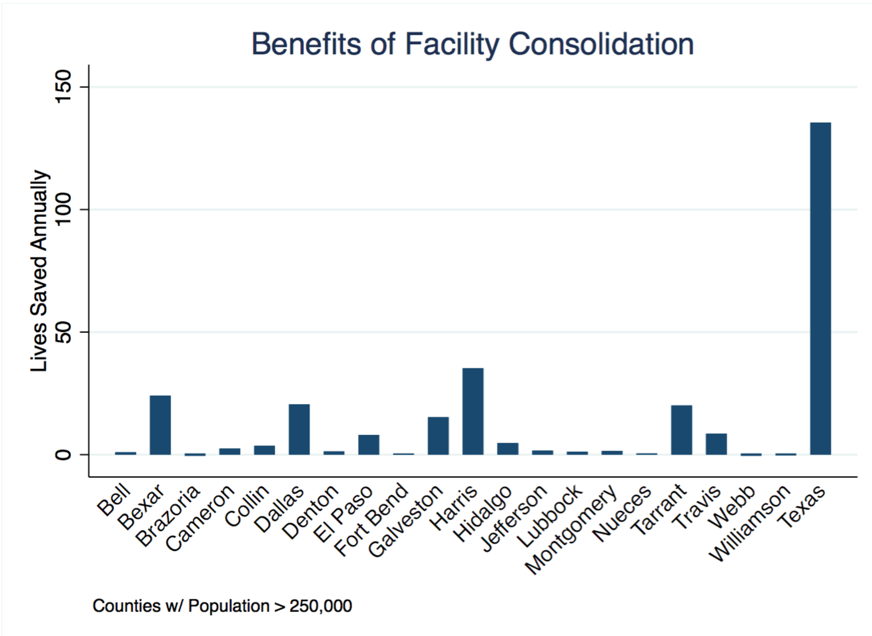



Figure 2.5: Lives Saved by Centralizing Patient Care

quite large. (The rightmost column is the entire state *including* the counties listed separately to the left.) Nearly 150 lives could be saved under facility centralization, taking advantage of the effects of learning by doing through volume and the attendant reductions in mortality. Valuing each life lost at $7,000,000 per [117] suggests gains of slightly more than 1 billion dollars annually just from centralizing patient care.

There are instructive examples outside the US context where care has been centralized and outcomes improved, both in the context of perinatal care and outside it. For example, [80] and [25] report on the results of a program of perinatal centralization begun in Portugal in 1989. Hospitals with fewer than 1500 deliveries annually had their obstetrics wards closed, intensive care units were added to higher-delivery-volume hospitals, a system of Level designation (matching the I-III system used here) was implemented, requirements for specialized staffing were imposed, a set of rules for referring patients to Level II and III centers created and a national transportation network created.[1] This system led to substantial improvements in the infant mortality rate in Portugal. More importantly, the position of Portugal *relative* to its European neighbors also improved substantially. In 1985, Portugal was an infant mortality outlier, with a mortality rate of 18/1000 infants, against a 15-country European average of about 10/1000 (and higher than any country in that group). By 2005, the mortality rate had declined to below 4/1000. Portugal's infant mortality rate in 2005 was bested only by Luxembourg, Finland and Sweden, three much richer states. (The source for the information in this paragraph is [81].)

For another instructive example in a case where transportation costs are an even greater consideration, [77] report on the results of an experiment to centralize the provision of stroke care in Manchester and London (separately). The number of hospitals in the greater London area providing stroke care declined as a result of this centralization from 30 to eight. Nevertheless, mortality declined in London at 3, 30 and 90 days. (Mortality was unaffected in Manchester.) This is particularly impressive, given that time out of the hospital means further brain death in the case of stroke. While labor and delivery can take multiple hours, minutes of delay can lead to significant negative outcomes for stroke patients. This makes the improvement in mortality from centralizing stroke care more impressive.

Both of these examples suggest that these policies can be implemented successfully and that they can make an important difference. The gains from centralization are substantial. Not considered in the present paper are several countervailing effects, some of which are

[1] Portugal is a small country, but the national perinatal system includes air transportation for patients from Madeira and the Azores, two island chains which are 500 and 850 miles from the mainland, respectively.

relevant only in the US context. Portugal and the UK both have national health insurance schemes: there is no role for negotiation between hospitals and insurers and there is no reason to worry about firm market power. Permitting only one firm to offer this highly-desirable service in the US context would give that firm substantial bargaining power in negotiations with insurers. It is possible that the firm's bargaining power would be high enough to extract all of this surplus. Furthermore, requiring each patient who needs this service to drive to a single hospital may increase traveling distances in some markets. The policy effects are considered at length in [15]. What I find there is that, at least for the issue of the costs of travel, the implied price per mile of additional distance has to be implausibly large (e.g., on the order of $10,000 per mile for the Austin market) to make this change welfare neutral.

Another policy option which I discuss in [15] is the possibility that the regulator should simply regulate the price of this service directly. If there is no substitute - conditional on staffing and available technology - for actually treating patients in the learning process, then a regulator may overlook the increase in market power that comes from being a monopoly provider of a service. However, this does not mean the regulator must sit passively while a hospital charges a monopoly price for the service. Prices can themselves be subject to regulation.

National health insurance schemes internalize this process, but there is an instructive example in the US from Maryland. [58] describes this program in great detail and is the source for the following information. The essential point is that Maryland regulates hospital charges across all payer types. This system has been in operation since the 1970's. In recent years the state has actually set *total revenue* for all hospitals in the state, computed relative to revenues in a base year, allowing for certain increases. Any adjustments and rates of growth in this number are also set by the state's Health Services Cost Review Commission. Hospital charges for particular services are set by the commission so that the expected revenues across service types given expected patient volumes add up to the global budget. The public payers are permitted a discount on charges relative to private payers, but this discount is small (about 6%). Several university medical centers (University of Maryland and several campuses of the Johns Hopkins system) are exempt from parts of this regulation, but otherwise hospital prices at all of the roughly 50 hospitals in the are regulated in Maryland on a much more stringent basis than in most other states in the US.

A regulator approaching this problem might view the idea of centralizing service and restricting entry as a gift to the designated facility. Prices would likely end up being higher due to the increase in bargaining power for this single hospital. However, prices are observable and regulable. Quality in this setting is not. The production of quality requires an extremely scarce input with an inelastic supply. (Obviously even if supply were elastic it would not be welfare-improving to increase it!)

## 2.8 Conclusion

The results in this paper suggest an important role for volume in the production of high-quality outcomes in the context of neonatal intensive care. Simply moving patients treated in the lowest volume NICU's to the highest on a per-county basis would save 140 lives annually in Texas. This may well be an underestimate, as the model was estimated on a set of realized patient volumes which are below the equilibrium which would prevail if there were fewer Level 3 facilities in the market. Furthermore, I do not consider the benefits of consolidating facilities across counties: Travis County (including Austin) is bordered by seven less populous counties - transferring patients from, e.g., Williamson and Hays counties to Travis county hospitals would both reduce the number of patients in those counties being seen at low volume facilities *and* further increase the volume at the designated Travis County NICU.

Overall, besides the current project there are useful examples of service regionalization in medical care in other parts of the world which can serve as an instructive example for efforts within the United States. While US regulators face a different set of challenges involving determining how to weigh factors such as price not present in countries with national health insurance systems, there is reason to believe that regulators here possess a set of tools which would enable them to take advantage of the positive effects of patient volume while still protecting consumers from monopoly behavior. The savings in lives in Texas alone are on the order of $1,000,000,000 per year.

# Chapter 3

# NICU Investment and Aggregate Outcomes

## 3.1 Introduction

The effects of investment in neonatal intensive care on outcomes for infants needing this service have been studied in a wide variety of papers, including [13], [8], [28], [65], [66], [88], [89], among others. The rate of admission to NICUs has been rising [?]. This rise is unlikely to be driven by increased need for the service: over the period 2007-2012 studied in [?], the average patient admitted to the NICU became larger and less likely to be premature. Most infants who are admitted to the NICU are admitted due to being premature or low birth weight. Admission rates are more likely driven by an increase in the available beds and the desire of hospitals to fill the beds.

Existing work, including [88] and others documents that there are important relationships between the volume of procedures performed in the NICU and the quality of the outcome, generally assessed via the mortality rate for admitted patients. Existing work makes it clear that infants are better off being served in hospitals which see higher volumes of patients, all else equal. This suggests, however, that entry into the intensive care market is potentially a cause for concern. In the current paper, I assess the effects of entry of intensive care units on a variety of outcomes, using data at the county level for every county in the US.

Hospitals make these investments since they know that NICU services are attractive to patients. In related work, I show in [15] that patients place a high valuation on intensive care services, whether they are likely to need them or not. Across different Diagnosis Related Group (DRG) categories, patients value the presence of a NICU. This includes patients whose infants are in the least severe group at birth, who are both the most numerous and the least likely to need NICU services. Patients care substantially more about the presence of a NICU than they care about their own driving distance to the hospital, which is typically one of the more important inputs to the patient's choice.

Hospitals react rationally to the fact that patients value a service. In a two hospital market, if Hospital $A$ has a NICU and Hospital $B$ does not, the fact that Hospital $A$ will perceive that it is losing patients to Hospital $B$ as a result of not having a NICU will make the investment very attractive. The costs of investing are not so high that the cost of doing so is prohibitive. The costs of investment which I found in [15] are well within the ability of most hospitals to make. The value of doing so to Hospital $B$ is clear: more patients who would otherwise have gone to Hospital $A$ will now instead choose to go to Hospital $B$. This generates revenue to $B$ from two sets of patients: patients who do not need NICU services and patients who do need NICU services. Previously Hospital $B$ would have transferred such patients to $A$. Having invested in a NICU, $B$ no longer needs to transfer patients and may instead treat them in-house, capturing the lost revenue from providing those services.

However, the incentives of hospitals to invest are problematic from the point of view of aggregate social welfare. If every hospital in a market invests in neonatal intensive care, average patient volumes per NICU will fall, since the number of patients who 'need' the service is to a first approximation fixed (the number of low birth weight patients is roughly constant from year to year - values are reported for Texas in [16]). As average volumes fall and quality decreases, the average mortality rate in the whole market increases. This is an important cost to free entry in this market which has not been adequately addressed by policymakers.

An existing literature on "supplier induced demand" suggests that hospitals may also take more aggressive steps to fill beds, once they exist. In the context of the previous example, once Hospital $B$ builds its NICU, it will likely discover means to fill the available beds. This is likely to include admitting patients who are more marginal to the treatment. That will involve admitting patients to the NICU who are born at higher birth weights, an effect noted by [?]. Another way to generate more patients to the NICU is to increase the rate at which Cesarean sections are performed in the hospital. Those infants are admitted to the NICU at a higher rate. Patients who are more marginal to needing a Cesarean section are likely to find that doctors are more interested in performing one when their hospital has a NICU.

The best tool available to prevent excessive entry into this market is Certificate of Need regulation. In many states, entry by hospitals into new markets (and entry of completely new hospital facilities) is regulated by a state board. These state boards are required to approve any investment by any hospital. While there many be important negatives associated with the existence of Certificate of Need regulation, including the fact that these boards may be subject to regulatory capture, or the fact that preventing entry into the NICU market (or any other market) gives the incumbent an important measure of market power, it is an important question whether the potential negatives associated with entry outweigh the positives.

In this paper, I will look at the effects of entry by NICUs on a variety of outcomes, including total mortality among very-low birth weight infants and the mortality rate among the same, total mortality and mortality rates among low birth weight infants, the number of Cesarean sections and the Cesarean section rate (as a fraction of all births) and the effects on total mortality among infants and total mortality rates. I will examine how these outcomes change as a function of both entry by NICUs, exit by NICUs and the total number of NICUs in the market. I will consider the role for regulation in improving outcomes in this market.

## 3.2 Related Literature

There is a large literature on the topic of volume and quality of outcome in NICUs. The topic of outcomes for low and very-low birth weight infants also attracts a substantial amount of attention, due to the tremendous importance of this population in determining the total number of infants who die prior to one year of age in the US every year. Generally about 1.5% of all infants born every year are very-low birth weight, but this group makes up more than half of the total number of infants who die every year ([16]). Some trends in this population are tracked in [66].

There are at least two potential channels for harm via NICU entry, both of which have been considered in different papers. First of all, there is a role for the volume of procedures in generating higher quality outcomes. Given that effect, which is studied in several papers including [88], [89] and [13], entry may have negative effects by reducing patients volumes within the NICU. A separate channel for negative effects involves a role for NICU levels. In particular, the diffusion of lower-level (in a sense to be defined later) NICUs in a market means that some women end up receiving treatment in hospitals which are not fully equipped to provide care to them. The importance of this channel is the subject of some debate: for several approaches to the topic see [8], []freedman2012 or [88]. The level channel is also discussed in [28].

A regulator wishing to concentrate patient volumes and take advantage of volume effects would create a “regionalization” plan. Such arrangements exist beyond neonatal intensive care and generally call for designating particular hospitals to be the highest-level provider of a particular service. Other hospitals may provide lower levels of the same service and must have in place arrangements to transfer patients to the highest level provider when that is necessary. For discussion of this in the context of neonatal intensive care, see [65].

There is similarly an enormous literature in the medical services research area on volume effects and the quality of outcomes across a wide range of different areas of medical care. Generally, though not always, the result found is that higher volumes lead to better quality outcomes, where “better quality” can be measured in terms of mortality rates, rates of complications, lower costs, etc. For a survey of some of this literature, see [83].

Inferring the direction of causality in this case can be quite difficult. For a survey of the complexities involved in doing so, see [69]. The complication is principally that we would expect that unobservably sicker patients who be sent to unobservably better hospitals. This makes both volume and the average mortality risk of the patients endogenous to an unobserved hospital quality parameter. Inferring causal effects is quite difficult. For an attempt at doing so using instrumental variables techniques in the context of neonatal intensive care in Texas, see my related work [16]. For more examples of this work in economics with similar approaches to instrumenting for patient volume, see [54], [45] or [44].

To my knowledge there is not previous existing work on the effect of entry by NICUs on the rate of Cesarean sections within the market. [?] is a recent paper which considers the effect of a policy change in Texas which ended reimbursement under the state Medicaid program for early elective C. sections. She found that the change in reimbursement policy did reduce C. sections among the Medicaid population (the group at which the policy change was directed), but found evidence of increases in the rate of C. sections among the privately insured populations, suggesting that doctors may be targeting an annual income (C. sections reimburse at higher rates than conventional deliveries among both privately and publicly insured patients). This relates to the literature on physician-induced demand for services, including [?].

On the regulatory side, there is a parallel between proposals in the health services research context to regionalize patient care and an earlier literature on the regulation of natural monopolies. A long literature on the regulation of such monopolies points to the sub-additivity of the cost function as the crucial feature (see the surveys in [?] and [?]); the key feature in this market is super-additivity in the production of quality.

## 3.3 Industry Background

Neonatal intensive care services are provided to severely ill infants. The most common reason for admission to the NICU is low birth weight. NICUs are differentiated by levels, ordered by the sophistication of the service they provide. For the purposes of this paper, there are three levels: I, II and III.[1] Level I NICUs are standard labor and delivery wards

[1] Some classification schemes feature a fourth, higher level, but those units are extremely few in number and are not tracked separately in the data which I use.

handling uncomplicated deliveries, all of which have the ability to stabilize an infant who is low birth weight or unwell for some reason for transport to a higher level facility. Level II units provide more intense care than Level I units, but do not perform surgeries and are not able to provide indefinite mechanical ventilation. Level III units provide the highest-possible level of care: surgery, mechanical ventilation of unlimited duration, etc.

The technology of neonatal intensive care emerged in the latter half of the 20th century. The history of the NICU is recounted ably in [11], from which much of the account which follows is taken. Prior to that, infants who were born at low or very low birth weight were discharged home to their parents after birth. Nothing could be done for them medically, so they nearly inevitably died. Starting in the early 20th century, doctors in France and then in the United States discovered that incubating infants born at abnormally low weights made it possible to save a fraction of them. Infants born at low birth weights generally do not produce enough heat on their own to survive, so placing them in incubators enables many of them to survive until they reach a weight sufficiently high that they produce this heat on their own.

The medical profession was initially skeptical of the idea of placing infants in incubators, or of placing incubators in hospitals ([11]). The first "intensive care units" were for that reason not in hospitals. Some were in amusement park sideshows or at traveling fairs, where attendees could pay nominal sums to see "tiny infants". The infants themselves were cared for free of charge in these units. One of the first "units" of this type which existed on a more permanent basis was an attraction in Coney Island. For a fascinating account of this period in the history of the technology, see [84] or [90].

Investment by hospitals in this market is popular since, as noted above, patients place a high valuation on the service, whether they anticipate needing it or not. Hospitals accurately perceive this and, in markets where their investment is not restricted, have tended to enter the NICU market. CON restrictions, however, are effective at preventing entry where they exist. In Figure (3.1) I plot a count of the number of Level III NICUs in Texas, Georgia and Florida between 1992 and 2014. Georgia and Florida both have strict certificate of need control, while Texas does not. As is immediately visible in the figure, the number of NICUs has increased dramatically in Texas over the time period pictured while the number in Georgia and Florida has stayed flat. Georgia and Florida also regionalize care for these infants.

## 3.4 Data

I use two principal sources of data for this project. I use the American Hospital Association's Annual Survey of Hospitals to track investment in NICUs over time. I use the National Center for Health Statistics' Linked Birth Cohort files to track births, deaths and birth weights.

The AHA annual survey is a comprehensive survey of the nearly the entire universe of American hospitals. Each facility is surveyed every year and unique identifiers are assigned to each facility. This permits hospitals to be tracked across years. The period of the survey I use covers 2005 - 2010, which is the same period covered by the data from the National Center for Health Statistics. The survey asks both whether hospitals report having neonatal intermediate or intensive care units (corresponding to the Levels II and III definitions offered above, respectively) or whether they offer non-zero numbers of beds providing intensive or intermediate care. Nearly every hospital reports having non-zero beds at either level if and

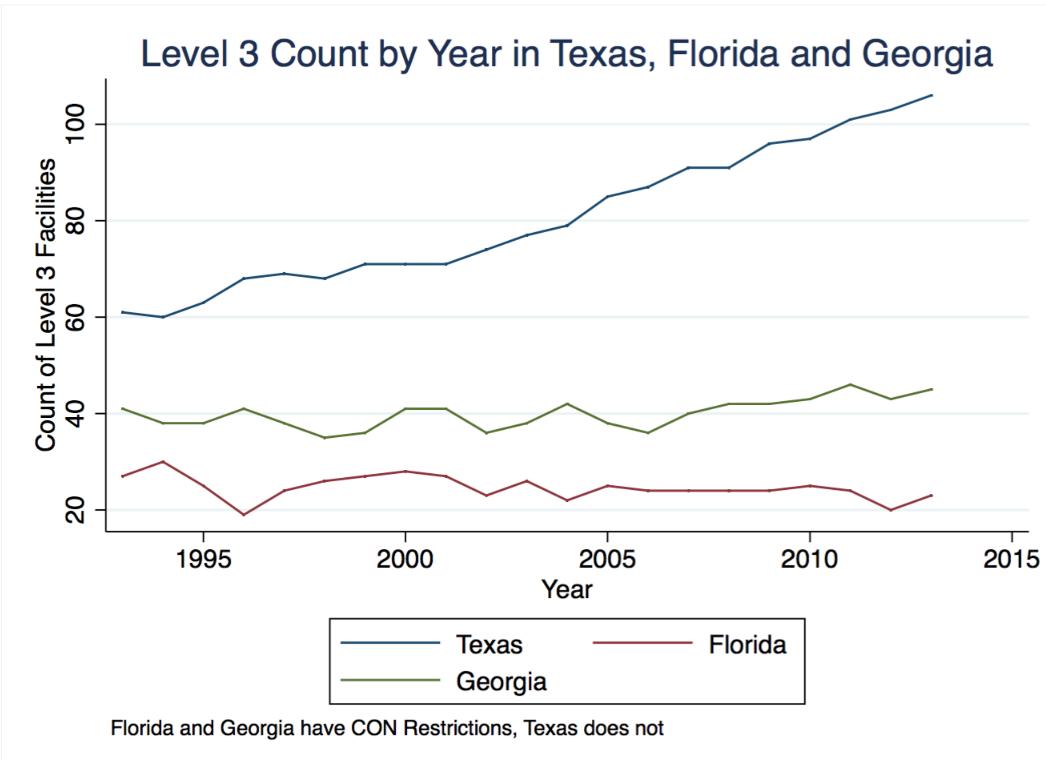



Figure 3.1: NICU Entry in Texas, Georgia and Florida, 1992 - 2013

only if it reports having the corresponding unit, but if the value of the unit indicator is missing in any year I assume the units were present if the number of beds offered is reported to be non-zero. The Annual Survey also includes the state and county in which each facility is located. This permits me to count the number of Level II and Level III units at each hospital in the data for the whole period I study. When numbers change from year to year, I infer that entry or exit have occurred.

Data from the National Center for Health Statistics covers nearly all infants born in the United States each year. Each record is derived from birth certificate data reported by the states. All states report the data and most states report 100% of all infants born in a given year. Birth certificate data is matched by the NCHS with death certificate data, where it is again possible in nearly every state to match 100% of the records from the year. Records include a wide range of information about the mother, father and the infant. For the purposes of the current project, relevant information includes the birth weight of the child (in grams), whether the child died, and how the baby was delivered (i.e., vaginally or via Cesarean section). The version of the data I use also includes information about the state and county of birth. This permits me to count the number of infants who are low or very low birth weight at the level of a county for each year between 2005 and 2010.

For each county in the country, I create a panel over the six years 2005 - 2010. In each year, I compute the total number of infants born at low and very low birth weight ( $<$ 2500 and 1500 grams, respectively) and compute the mortality rate within each group. For the two groups, I compute mortality rates taking as the denominator the set of all births in that county or just the set of LBW and VLBW infants. I also compute the overall mortality among all groups (i.e., including those who are not low birth weight). Finally, I compute the count of Cesarean sections and the rate at which they are performed. I see how these outcomes vary as a function of the number of units at Levels II and III, plus entry or exit by the same.

## 3.5 VLBW Mortality

This section covers mortality among the very low birth weight, including the following Tables:

- Table 3.1 Entry of Level 3 on VLBW Mortality
- Table 3.2 Entry of Level 2 on VLBW Mortality
- Table 3.3 Total Level 3 on VLBW Mortality
- Table 3.4 Total Level 2 on VLBW Mortality
- Table 3.5 Exit of Level 3 on VLBW Mortality
- Table 3.6 Exit of Level 2 on VLBW Mortality

Effects on the mortality of very low birth weight infants due to entry of Level II or Level III facilities suggest that there is not a strong effect on mortality in the specifications used here. Controlling for state and year fixed effects suggest that entry of a Level II or Level III facility increases mortality in this population, as can be seen in Tables 3.1 and 3.2, but after controlling for a county specific term the effect mostly vanishes. This may be because there is little variation in entry in the time period studied and not very much variation in

| | (1) VLBW Mort. | (2) VLBW Mort. | (3) VLBW Mort. |
|---|---|---|---|
| Entry 3 | 38.8481*** | 35.7390*** | -0.3183 |
| | 1.2110 | 1.1941 | 0.2265 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.1: Entry of Level 3 on VLBW Mortality

| | (1) VLBW Mort. | (2) VLBW Mort. | (3) VLBW Mort. |
|---|---|---|---|
| Entry 2 | 33.3243*** | 30.3766*** | 0.0429 |
| | 1.2170 | 1.1975 | 0.2203 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.2: Entry of Level 2 on VLBW Mortality

the number of very-low birth weight infants at the level of each county, so the number of deaths is likely to be small.

Effects on the mortality of VLBW infants from the total numbers of facilities in Tables (3.3) and( 3.4) at Levels II and III paint a similar picture. While there is limited support for the claim that the total number of Level II and Level III units lead to more deaths among very-low birth weight infants the effects are hard to see when controlling for fixed effects at the level of a county.

Exit of either a Level II or a Level III unit from the markets studied here shown in

| | (1) VLBW Mort. | (2) VLBW Mort. | (3) VLBW Mort. |
|---|---|---|---|
| Total 3 | 14.3707*** | 14.4835*** | 0.0936 |
| | 0.0756 | 0.0769 | 0.1443 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.3: Total Level 3 on VLBW Mortality

| | (1) VLBW Mort. | (2) VLBW Mort. | (3) VLBW Mort. |
|---|---|---|---|
| Total 2 | 20.3036*** | 20.7659*** | 0.6531*** |
| | 0.1728 | 0.1749 | 0.1438 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4: Total Level 2 on VLBW Mortality

Tables (3.5) and (3.6) show only modest effects on mortality, though the effects run in the opposite direction to that predicted by the theory that there are important learning-by-doing effects at work. One important caveat in this is that it is impossible in any of the data to observe when during the year an exit occurs - the timing of the exit is likely to be important when there is an important role for forgetting, as was documented in [16]. The total number of exits is also likely to be low, given that these units do not frequently close.

| | (1) VLBW Mort. | (2) VLBW Mort. | (3) VLBW Mort. |
|---|---|---|---|
| Exit 3 | 44.0341*** | 40.3784*** | 1.2619*** |
| | 1.3061 | 1.2924 | 0.2457 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: Exit of Level 3 on VLBW Mortality

| | (1) VLBW Mort. | (2) VLBW Mort. | (3) VLBW Mort. |
|---|---|---|---|
| Exit 2 | 37.8466*** | 35.2810*** | 0.2763 |
| | 1.2542 | 1.2324 | 0.2309 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: Exit of Level 2 on VLBW Mortality

### 3.5.1 VLBW Mortality Rates among All Births

The current section considers the effects of entry, exit and the total number of facilities at Levels II and III on the mortality rate of very-low birth weight infants, where the rate is computed against the total population of all infants born in the county every year. This rate has the advantage of being more stable than the rate computed in the subsequent section. The issue is that the number of very low birth weight infants in any given market is likely to be low in a given year, so that the rate computed will vary quite a bit with a single additional death in the category. In this section, by computing very low birth weight mortality against all of the patients, the problem of instability is avoided, though now the problem is to an extent reversed: the rate compute can be insufficiently responsive to the number of deaths. This section includes the following Tables:

- Table 3.7 Entry of Level 3 on VLBW Mortality Rate Per Thousand Births
- Table 3.8 Entry of Level 2 on VLBW Mortality Rate Per Thousand Births
- Table 3.9 Total Level 3 on VLBW Mortality Rate Per Thousand Births
- Table 3.10 Total Level 2 on VLBW Mortality Rate Per Thousand Births
- Table 3.11 Exit of Level 3 on VLBW Mortality Rate Per Thousand Births
- Table 3.12 Exit of Level 2 on VLBW Mortality Rate Per Thousand Births

The effects are not significant over most of the specifications and outcomes measured here in Tables (Table 3.7) - (Table 3.12) . There is not very much evidence for a strong effect in this area. The standard errors tend to include zero across the various specifications. As

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Entry 3 | -2.3248 | -2.1640 | -0.1454 |
| | 2.7237 | 2.7446 | 2.9103 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.7: Entry of Level 3 On VLBW Mortality Rate Per Thousand Births

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Entry 2 | -2.4840 | -2.3688 | 0.0658 |
| | 2.7112 | 2.7285 | 2.8303 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.8: Entry of Level 2 on VLBW mortality rate per Thousand Births

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Total 3 | -0.3568 | -0.2126 | 0.1481 |
| | 0.3131 | 0.3252 | 1.8535 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.9: Total Level 3 on VLBW Mortality Rate Per Thousand Births

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Total 2 | -0.8107 | -0.7092 | -0.1054 |
| | 0.5314 | 0.5556 | 1.8490 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.10: Total Level 2 on VLBW Mortality Rate Per Thousand Births

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Exit 3 | -2.2320 | -1.7878 | -0.0836 |
| | 2.9485 | 2.9789 | 3.1594 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.11: Entry of Level 3 On VLBW Mortality Rate Per Thousand Births

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Exit 2 | -2.7169 | -2.4897 | -0.2596 |
| | 2.8094 | 2.8252 | 2.9668 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.12: Entry of Level 2 on VLBW mortality rate per Thousand Births

mentioned above, this is in part due to the fact that the very-low birth weight population is about 1.5% of all births (nationally), and then the subset of infants who die in this group is much smaller. The effect being examined in these regressions is quite small in the best case because the denominator (all births) is so much larger than the numerator (deaths among a subset of 1.5% of the denominator). It is not terribly surprising that it is hard to see any effect.

### 3.5.2 VLBW Mortality Rates Among VLBW Births

This section covers mortality rates among very-low birth weight infants only, including the following Tables:

- Table 3.17 Entry of Level 3 on Mortality Rate Among VLBW
- Table 3.18 Entry of Level 2 on Mortality Rate Among VLBW
- Table 3.15 Total Level 3 on Mortality Rate Among VLBW
- Table 3.16 Total Level 2 on Mortality Rate Among VLBW
- Table 3.17 Exit of Level 3 on Mortality Rate Among VLBW
- Table 3.18 Exit of Level 2 on Mortality Rate Among VLBW

The effects of entry, exit and the total number of facilities at Levels II and III are outlined in Tables (3.17) - (3.18). Here I have limited to looking at the mortality rate of very low birth weight infants among the total population of very low birth weight infants, rather than the total number of births every year. Here the results are more suggestive of a positive effect of entry, where both entry in Table (3.17) and the total number of Level III units in Table ( 3.15) are associated with lower mortality rates among the very low birth weight group. In most county markets, however, the total number of very low birth weight infants every year is going to be low, so the rates will be unstable due to a "small denominator" problem: with three total very low birth weight infants in a given county market, the rate will be very sensitive to a single additional death.

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Entry 3 | -88.1778*** | -77.1822*** | -7.4510 |
| | 17.4677 | 17.5246 | 17.9334 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.13: Effect of Level 3 Entry on Mortality Rate Among VLBW

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Entry 2 | -62.0273*** | -54.5079** | 1.4509 |
| | 17.4487 | 17.4425 | 17.5260 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.14: Effect of Level 2 Entry on Mortality Rate Among VLBW

| | (1) | (2) | (3) |
|---|---|---|---|
| | VLBW MR | VLBW MR | VLBW MR |
| Total 3 | -21.1686*** | -20.6812*** | -4.3977 |
| | 2.0185 | 2.0888 | 11.3966 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.15: Effect of Total 3 on Mortality Rate Among VLBW

| | (1) VLBW MR | (2) VLBW MR | (3) VLBW MR |
|---|---|---|---|
| Total 2 | -27.4827*** | -26.0075*** | -6.6002 |
| | 3.4520 | 3.5833 | 11.3981 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.16: Effect of Total 2 on Mortality Rate Among VLBW

| | (1) VLBW MR | (2) VLBW MR | (3) VLBW MR |
|---|---|---|---|
| Exit 3 | -69.3765*** | -61.9221** | 16.3818 |
| | 19.0254 | 19.1402 | 19.5815 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.17: Effect of Level 3 Exit on Mortality Rate Among VLBW

| | (1) VLBW MR | (2) VLBW MR | (3) VLBW MR |
|---|---|---|---|
| Exit 2 | -65.7772*** | -56.7633** | 5.0067 |
| | 18.2346 | 18.2374 | 18.5014 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.18: Effect of Level 2 Exit on Mortality Rate Among VLBW

## 3.6 LBW Mortality

This section considers mortality rates among low birth weight infants ($< 2500$ grams), a category which includes the very-low birth weight infants above (those weighing less than 1500 grams). This section includes the following Tables:

- Table 3.23 Entry of Level 3 on LBW Mortality
- Table 3.24 Entry of Level 2 on LBW Mortality
- Table 3.21 Total Level 3 on LBW Mortality
- Table 3.22 Total Level 2 on LBW Mortality
- Table 3.23 Exit of Level 3 on LBW Mortality
- Table 3.24 Exit of Level 2 on LBW Mortality

Entry of facilities at Levels II and III shows similar effects on mortality as those seen in the mortality of VLBW infants. In Tables (3.23) and (3.24) the effects are positive in two specifications, though not when including controls for each specific county. This is compatible with the idea that volumes decrease, skill depreciates, and additional patients die due to lower patient volumes.

In the cases of total numbers of Level II and Level III facilities described in Tables (3.21) and (3.22) we find similar support for this theory. Higher numbers of each facility are associated with higher mortality rates, though these effects are no longer present once we control for fixed effects at the county level, where there is little variation left in the data at

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW Mort. | LBW Mort. | LBW Mort. |
| Entry 3 | 49.0003*** | 45.1010*** | -0.6112* |
| | 1.5125 | 1.4922 | 0.2525 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.19: Entry Level 3 on LBW Mortality

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW Mort. | LBW Mort. | LBW Mort. |
| Entry 2 | 41.6122*** | 37.9721*** | -0.2078 |
| | 1.5211 | 1.4975 | 0.2456 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.20: Entry Level 2 on LBW Mortality

| | (1) LBW Mort. | (2) LBW Mort. | (3) LBW Mort. |
|---|---|---|---|
| Total 3 | 18.1937*** | 18.3470*** | 0.2840 |
| | 0.0912 | 0.0929 | 0.1608 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.21: Total 3 on LBW Mortality

| | (1) LBW Mort. | (2) LBW Mort. | (3) LBW Mort. |
|---|---|---|---|
| Total 2 | 25.4366*** | 26.0629*** | 0.6716*** |
| | 0.2154 | 0.2179 | 0.1603 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.22: Total 2 on LBW Mortality

such a small geographic unit. But there is suggestive evidence that some of the effects may be present.

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW Mort. | LBW Mort. | LBW Mort. |
| Exit 3 | 55.2185*** | 50.6135*** | 1.3773*** |
| | 1.6320 | 1.6158 | 0.2738 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.23: Exit Level 3 on LBW Mortality

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW Mort. | LBW Mort. | LBW Mort. |
| Exit 2 | 47.9651*** | 44.7827*** | 0.4704 |
| | 1.5660 | 1.5396 | 0.2574 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13667 | 13667 | 13667 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.24: Exit Level 2 on LBW Mortality

### 3.6.1 LBW Mortality Rate among All Births

The following section discusses the mortality rate among low birth weight infants against the total population of all births. As before, there is the caveat that these rates are likely to be "too stable": insufficiently responsive to a few additional deaths, in contrast to the previous section where rates are unstable. This section concerns the following Tables:

- Table 3.29 Entry of Level 3 on Mortality Rate of LBW Per Thousand Births
- Table 3.30 Entry of Level 2 on Mortality Rate of LBW Per Thousand Births
- Table 3.27 Total Level 3 on Mortality Rate of LBW Per Thousand Births
- Table 3.28 Total Level 2 on Mortality Rate of LBW Per Thousand Births
- Table 3.29 Exit of Level 3 on Mortality Rate of LBW Per Thousand Births
- Table 3.30 Exit of Level 2 on Mortality Rate of LBW Per Thousand Births

The effects sizes here are mostly estimated to be right around 0. Confidence intervals include zeros across most of the specifications and outcomes considered. This is likely in part because the rates are quite stable, given that the percentage of infants who are low birth weight is relatively low (generally less than 10% annually) and the number of deaths among this population is also quite low, so the effect size we are searching for is a small change in a subset of a subset of the much larger population of all births in the market.

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW MR | LBW MR | LBW MR |
| Entry 3 | -2.7589 | -2.4936 | -0.1221 |
| | 3.0068 | 3.0277 | 3.1828 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.25: Entry of Level 3 on Mortality Rate of LBW Per Thousand Births

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW MR | LBW MR | LBW MR |
| Entry 2 | -3.0452 | -2.8319 | -0.0087 |
| | 2.9929 | 3.0100 | 3.0952 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.26: Entry of Level 2 on Mortality Rate of LBW Per Thousand Births

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW MR | LBW MR | LBW MR |
| Total 3 | -0.4284 | -0.2518 | 0.1602 |
| | 0.3456 | 0.3587 | 2.0270 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.27: Total Level 3 on Mortality Rate of LBW Per Thousand Births

| | (1) LBW MR | (2) LBW MR | (3) LBW MR |
|---|---|---|---|
| Total 2 | -0.9770 | -0.8448 | -0.1312 |
| | 0.5866 | 0.6129 | 2.0221 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.28: Total Level 2 on Mortality Rate of LBW Per Thousand Births

| | (1) LBW MR | (2) LBW MR | (3) LBW MR |
|---|---|---|---|
| Exit 3 | -2.6408 | -1.9883 | -0.0540 |
| | 3.2549 | 3.2862 | 3.4552 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.29: Exit of Level 3 on Mortality Rate of LBW Per Thousand Births

| | (1) LBW MR | (2) LBW MR | (3) LBW MR |
|---|---|---|---|
| Exit 2 | -3.1556 | -2.7629 | -0.2221 |
| | 3.1014 | 3.1166 | 3.2445 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 3.30: Exit of Level 2 on Mortality Rate of LBW Per Thousand Births

### 3.6.2 LBW Mortality Rate Among LBW Births

This section considers the effects of entry, exit and the total numbers of facilities at Levels II and III on the mortality rate among the low birth weight only. These measurements will likely suffer from a similar problem as those in the similar section for very low birth weight infants above, though the problem is alleviated somewhat because the low birth weight group is a larger percentage of the total number of infants born every year, generally somewhere around 10%. While there will be some instability in the computed rates here, rates are more stable than those computed for the very-low birth weight infants. This section includes the following Tables:

- Table 3.35 Entry of Level 3 on Mortality Rate Among LBW
- Table 3.36 Entry of Level 2 on Mortality Rate Among LBW
- Table 3.33 Total Level 3 on Mortality Rate Among LBW
- Table 3.34 Total Level 2 on Mortality Rate Among LBW
- Table 3.35 Exit of Level 3 on Mortality Rate Among LBW
- Table 3.36 Exit of Level 2 on Mortality Rate Among LBW

Here the measured effect sizes for specifications including controls only for the year and state suggest a positive effect from additional entry of Level II or III facilities. Entry has a negative effect on the mortality rate among this group. However, this effect vanishes when controls for the county are included. The signs may be negative but the standard errors are wide and comfortably include 0.

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW MR | LBW MR | LBW MR |
| Entry 3 | -138.7689*** | -124.0044*** | -13.6939 |
| | 23.6416 | 23.7731 | 24.9643 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.31: Effect of Entry of Level 3 on Mortality Rate Among LBW

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW MR | LBW MR | LBW MR |
| Entry 2 | -115.9300*** | -104.1384*** | -18.0991 |
| | 23.6124 | 23.6594 | 24.3964 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.32: Effect of Entry of Level 2 on Mortality Rate Among LBW

| | (1) | (2) | (3) |
|---|---|---|---|
| | LBW MR | LBW MR | LBW MR |
| Total 3 | -35.4795*** | -34.1961*** | -6.9902 |
| | 2.7239 | 2.8269 | 15.8648 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.33: Effect of Total Level 3 on Mortality Rate Among LBW

| | (1) LBW MR | (2) LBW MR | (3) LBW MR |
|---|---|---|---|
| Total 2 | -46.9516*** | -44.0454*** | -12.8614 |
| | 4.6643 | 4.8547 | 15.8665 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.34: Effect of Total Level 2 on Mortality Rate Among LBW

| | (1) LBW MR | (2) LBW MR | (3) LBW MR |
|---|---|---|---|
| Exit 3 | -112.0474*** | -100.5398*** | 14.2475 |
| | 25.7550 | 25.9699 | 27.2596 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.35: Effect of Exit of Level 3 on Mortality Rate Among LBW

| | (1) LBW MR | (2) LBW MR | (3) LBW MR |
|---|---|---|---|
| Exit 2 | -104.7596*** | -93.8885*** | 6.3231 |
| | 24.6853 | 24.7447 | 25.7553 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 8468 | 8468 | 8468 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.36: Effect of Exit of Level 2 on Mortality Rate Among LBW

## 3.7 Number of Cesarean Sections

This section considers the effects of entry, exit and the total numbers of facilities at Levels II and III on the number of Cesarean sections which are performed in the market. The Tables discussed in this section are the following:

- Table 3.41 Entry of Level 3 on C-Sections
- Table 3.42 Entry of Level 2 on C-Sections
- Table 3.39 Total Level 3 on C-Sections
- Table 3.40 Total Level 2 on C-Sections
- Table 3.41 Exit of Level 3 on C-Sections
- Table 3.42 Exit of Level 2 on C-Sections

The effects of entry on the number of C. sections in Tables (3.41) and (3.42) suggest different things depending on the precise specification, since the sign of the main effect changes. It is not possible on the basis of these results to form a clear conclusion about the way C. section totals are affected by the entry of an additional facility at either level. The effects of the total number of facilities on the outcome in Tables (3.39) and (3.40) are more consistent with the story, in that both suggest increases in the number of C. sections as facility counts increase. It may be that there is an issue here from not knowing the exact timing of entry during the year in making the conclusion that additional facilities increase C. section numbers.

| | (1) C. Sect. | (2) C. Sect. | (3) C. Sect. |
|---|---|---|---|
| Entry 3 | 3393.6825*** | 3042.9344*** | -1.3293 |
| | 106.0003 | 103.1548 | 6.6090 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.37: Entry of Level 3 on C-Sections

| | (1) C. Sect. | (2) C. Sect. | (3) C. Sect. |
|---|---|---|---|
| Entry 2 | 2802.8565*** | 2475.1023*** | -15.4585* |
| | 106.7386 | 103.6288 | 6.4256 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.38: Entry of Level 2 on C-sections

| | (1) C. Sect. | (2) C. Sect. | (3) C. Sect. |
|---|---|---|---|
| Total 3 | 1350.2811*** | 1341.3620*** | 70.3634*** |
| | 5.1128 | 5.1701 | 4.1561 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.39: Total Level 3 on C-Sections

| | (1) | (2) | (3) |
|---|---|---|---|
| | C. Sect. | C. Sect. | C. Sect. |
| Total 2 | 1711.6750*** | 1722.5540*** | 51.5792*** |
| | 15.6637 | 15.6844 | 4.1704 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.40: Total Level 2 on C-Sections

| | (1) | (2) | (3) |
|---|---|---|---|
| | C. Sect. | C. Sect. | C. Sect. |
| Exit 3 | 3736.4798*** | 3298.6132*** | 2.4295 |
| | 114.5982 | 111.9683 | 7.1746 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.41: Exit of Level 3 on C-Sections

| | (1) | (2) | (3) |
|---|---|---|---|
| | C. Sect. | C. Sect. | C. Sect. |
| Exit 2 | 3288.3675*** | 3013.9848*** | -2.7543 |
| | 109.8176 | 106.4363 | 6.7372 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.42: Exit of Level 2 on C-sections

### 3.7.1 C-Section Rates

In the current section, we consider the effects of entry, exit and the total number of facilities at each of Levels II and III on the rate at which C. sections are performed in the market. The computation of this rate should not be subject to the instability or excessive stability problems seen when similar comparisons were made of the outcomes for low and very-low birth weight infants above, since the number of women getting C. sections annually is very much larger than the fraction of infants who are LBW or less. The Tables discussed in this section are:

- Table 3.47 Entry of Level 3 on CSection Rate
- Table 3.48 Entry of Level 2 on CSection Rate
- Table 3.45 Total Level 3 on CSection Rate
- Table 3.46 Total Level 2 on CSection Rate
- Table 3.47 Exit of Level 3 on CSection Rate
- Table 3.48 Exit of Level 2 on CSection Rate

In the preferred specification which controls for time trends and state and county fixed effects, there is no clear effect of any of the outcomes on the C. section rate. There are effects in other specifications only controlling for state and year effects, suggesting that entry does increase the rate at which these are performed, but trying to see this effect in aggregate data at the county level is challenging.

| | (1) | (2) | (3) |
|---|---|---|---|
| | CS Rate | CS Rate | CS Rate |
| Entry 3 | 67.6135*** | 61.6915*** | 0.3462 |
| | 8.0751 | 7.9763 | 3.9370 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.43: Effect of Level 3 Entry on CSection Rate

| | (1) | (2) | (3) |
|---|---|---|---|
| | CS Rate | CS Rate | CS Rate |
| Entry 2 | 68.2473*** | 57.3694*** | 0.3188 |
| | 8.0373 | 7.9318 | 3.8287 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.44: Effect of Level 2 Entry on CSection Rate

| | (1) | (2) | (3) |
|---|---|---|---|
| | CS Rate | CS Rate | CS Rate |
| Total 3 | 15.9777*** | 14.9948*** | 1.8786 |
| | 0.9206 | 0.9384 | 2.5072 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.45: Effect of Total Level 3 on CSection Rate

| | (1) CS Rate | (2) CS Rate | (3) CS Rate |
|---|---|---|---|
| Total 2 | 29.6970*** | 25.7336*** | 2.1259 |
| | 1.5590 | 1.6033 | 2.5011 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.46: Effect of Total Level 2 on CSection Rate

| | (1) CS Rate | (2) CS Rate | (3) CS Rate |
|---|---|---|---|
| Exit 3 | 67.0976*** | 59.7321*** | 0.3667 |
| | 8.7450 | 8.6610 | 4.2740 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.47: Effect of Level 3 Exit on CSection Rate

| | (1) CS Rate | (2) CS Rate | (3) CS Rate |
|---|---|---|---|
| Exit 2 | 67.7317*** | 59.0016*** | 0.2112 |
| | 8.3305 | 8.2131 | 4.0134 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.48: Effect of Level 2 Exit on CSection Rate

## 3.8 Overall Mortality Rate

Finally, I consider the effects of entry, exit and the overall numbers of Levels II and III on the overall mortality rate. This section includes the following Tables:

- Table 3.53 Entry of Level 3 on Total Mortality Rate
- Table 3.54 Entry of Level 2 on Total Mortality Rate
- Table 3.51 Total Level 3 on Total Mortality Rate
- Table 3.52 Total Level 2 on Total Mortality Rate
- Table 3.53 Exit of Level 3 on Total Mortality Rate
- Table 3.54 Exit of Level 2 on Total Mortality Rate

The effects in these Tables are not significant, except for a single specification in Table (3.51). The mortality rate may not vary that much from year to year within a given county, so the effect may be hard to see (or, indeed, absent). It is not clear that there is an important effect of any of these events on the measured outcomes. It is likely that in large counties with many births and deaths every year, the effect of entry of a single hospital, for example, will be on the order of several additional deaths a year at most, while the effects in small counties may be difficult to infer because the total number of deaths is in any case quite small. But it is not possible to claim with confidence that there is any effect on the overall mortality rate.

| | (1) Total MR | (2) Total MR | (3) Total MR |
|---|---|---|---|
| Entry 3 | -4.3406 | -3.8712 | -0.2616 |
| | 3.4956 | 3.5187 | 3.6861 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.49: Effect of Level 3 Entry on Total Mortality Rate

| | (1) Total MR | (2) Total MR | (3) Total MR |
|---|---|---|---|
| Entry 2 | -4.5162 | -3.9025 | -0.0848 |
| | 3.4795 | 3.4981 | 3.5847 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.50: Effect of Level 2 Entry on Total Mortality Rate

| | (1) Total MR | (2) Total MR | (3) Total MR |
|---|---|---|---|
| Total 3 | -0.7379 | -0.4485 | 0.3218 |
| | 0.4018 | 0.4169 | 2.3475 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.51: Effect of Total Level 3 on Total Mortality Rate

| | (1) Total MR | (2) Total MR | (3) Total MR |
|---|---|---|---|
| Total 2 | -1.5451* | -1.2862 | -0.1897 |
| | 0.6820 | 0.7123 | 2.3418 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.52: Effect of Total Level 2 on Total Mortality Rate

| | (1) Total MR | (2) Total MR | (3) Total MR |
|---|---|---|---|
| Exit 3 | -4.2817 | -3.4095 | -0.2894 |
| | 3.7841 | 3.8191 | 4.0015 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.53: Effect of Level 3 Exit on Total Mortality Rate

| | (1) Total MR | (2) Total MR | (3) Total MR |
|---|---|---|---|
| Exit 2 | -4.8488 | -4.2183 | -0.5277 |
| | 3.6056 | 3.6220 | 3.7576 |
| Year FE | Yes | Yes | Yes |
| State FE | No | Yes | No |
| County FE | No | No | Yes |
| N | 13666 | 13666 | 13666 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.54: Effect of Level 2 Entry on Total Mortality Rate

## 3.9 Policy Options

Given the evidence that there are potential negative effects from permitting free entry into the neonatal intensive care market, it is important to formulate an appropriate policy response. The most important tool available to regulators is "Certificate of Need" regulation. As noted above in connection to the discussion of Figure (3.1), where these programs exist it is clear that regulators can successfully prevent entry into the market.

The existence of an economy of scale in the production of quality suggests that entry restrictions may be warranted. The key question is whether the costs to consumers in the form of higher prices for NICU services are outweighed by the benefits to the same in the form of a lower mortality rate. The second of the two calculations is relatively easy to make: in [16] I estimate the magnitude of the externality that is imposed by additional entry by showing how patient mortality is affected by hospital volume within the NICU. Prices are generally not observed in this environment, whether the transacted prices actually paid by insurers to hospitals or the copayments of the patients to the hospitals. This presents a problem. In [15] I measure what can reasonably be viewed as a proxy for prices in order to get some measure of the market power that firms may gain by becoming the monopoly provider of NICU services in their markets. I find that firm pricing power likely increases in the worst case scenario (for consumers) by a factor of 2 - 2.5 at worst. This is not so large that firms can completely appropriate all of the surplus generated by lower mortality rates.

On the other hand, there are other tools at the disposal of the regulator here. In particular, a regulator can decide to directly regulate prices. Here there is a parallel to an earlier literature on the regulation of natural monopolies. In that case, the cost function of the natural monopolist is sub-additive (see [**?**]), so it satisfies

$$C(y) < \sum_{i=1}^{n} C(y_i),\ y = \sum_{i=1}^{n} y_i$$

That is, the cost of having one firm produce the total output $y$ is lower than the cost of having $n$ firms produce the same total quantity. In that case, it may make sense to have one firm produce the whole output rather than permitting $n$ firms to enter the market from the point of view of social efficiency. The present market is formally similar in that average quality is higher when one firm produces all of the output, rather than $n$ firms.

With that in mind, the regulator may wish to restrict entry into the market. However, the same regulator can potentially prevent some of the welfare loss associated with monopoly power by regulating prices directly. Even if the regulator does not attempt to ensure prices approach marginal cost (which is a difficult benchmark to achieve, especially under incomplete information), it is still likely possible to reduce the harm caused by monopoly pricing by mandating some price lower than the (observable) monopoly prices. Prices themselves are directly observable and regulable, whereas quality can only be produced with a crucial input with inelastic supply: more patients.

In my paper [16] I show that caring for patients in fewer NICUs in Texas could lead to a billion dollar welfare improvement annually in the form of lives saved. There may be similar savings to be realized in other large states. The savings over the entire country will likely be in the range of several billion dollars. This represents quite a substantial gain from restricting entry into this market.

## 3.10 Conclusion

In this paper I have considered the aggregate welfare implications of hospital investment in Neonatal Intensive Care across a variety of outcomes. Motivated by the observations that there are both important volume effects on producing high quality outcomes within a hospital and that there are strong incentives for hospitals to make an investment in this service, given that it is both attractive to patients an in itself lucrative, I study the fact that there may be "too much" entry into this service market. Across a wide range of outcomes, I found some suggestive evidence that there may be effects of entry on some of the outcomes, but overall the results are not clear enough to make the conclusion unambiguous. In future work, I propose to add more years to the data.

# Appendix

# Appendix 1

# Investment Appendix

## 1.1 NICU Capacity Constraints

Using birth certificate data with information about the hospital of birth, I can compute several measures of utilized capacity in NICU's. These measures show that capacity is not a binding constraint in almost any hospital in the state. Capacity constraints at the market level are not leading to the construction of new NICU's. It is possible using aggregate birth and NICU admission information at the level of entire counties to compute a measure of utilized days among all hospitals in the county, which is in Table (1.1). Total NICU admits at birth and total beds available are calculated from birth certificate data from the National Center for Health Statistics and the Annual Survey of Hospitals, respectively ([104]). I compute the number of bed-days available per year in each market and use birth certificate data to count the number of infants admitted to the NICU at birth in the same markets. I can then compute the number of bed-days available per admitted patient.

Average duration of stay per patient is not computable from any data I have since I do not observe dates of admission or discharge, but estimates exist in the literature. The National Perinatal Information Center reports that the average duration of stay in the NICU across all patients in the 2009-2010 year was 13.2 days ([74]). As is immediately visible in table (1.1), bed-days available per admit in every metro area far exceed this limit.

The birth certificate data enables me to count the number of patients admitted each month at each hospital in the data. This exercise provides a similar picture. I make three comparisons. First, I compare the total number of admissions of any duration to the NICU for the whole month to the number of beds. The results are in Table (1.5) in the second column. Only a third of hospital-month observations see more patients admitted to the NICU *for the whole month* than there are beds in the facility. Given the average duration of stay, it is very unlikely that a capacity constraint is reached in these months.

Second, I compute two related measures of capacity utilization. I suppose that each patient admitted to the NICU (or transferred in) stays for the either the average stay of 13.2 days, or double the average duration (26.4 days). I subtract this from the total number of bed-days available in the month and then divide by the number of beds available. This is a "free days per bed" measure. Columns 3 and 5 in Table (1.5) report mean free days per bed assuming 13.2 and 26.4 days per stay, respectively, while columns 4 and 6 report median free days per bed under the same assumptions. Even under the much more unrealistic, 26.4 days assumption, mean free days per bed are still positive, averaging about 4.25 for the eight years of the data. Assuming all stays are of average duration leaves on average 16.6 days per bed free for the same period.

These measure suggest that intensive care units are very unlikely to be capacity constrained in almost any month. Hospital investment is not being driven by capacity constraints at existing facilities in the market.

## 1.2 Computational Details

The number of distinct aggregate states of competitors across three different distance bins is given by the product of binomial coefficients

$$\binom{n_{0-5}+4-1}{n_{0-5}}\binom{n_{5-15}+4-1}{n_{5-15}}\binom{n_{15-25}+4-1}{n_{15-25}}$$

where $n_{x-y}$ is the number of firms at distances between $x$ and $y$ miles. This is the number of different ways to allocate $n_{x-y}$ firms to each of 4 categories (three levels and an exit state) where the number in any category is permitted to be 0.[1] I then take the product across the three distance bins. From the perspective of one of these competitors, in each of these aggregate states the firm itself can be at level 1, 2, 3 or out of the market. In the small two-competitor example above, the number of state elements would be: $\binom{0+4-1}{0}\binom{2+4-1}{2}\binom{0+4-1}{0} = 10 \times 4 = 40$.

For example, consider Knapp Medical Center in Weslaco, Texas (a one-hospital town of about 40,000 people near the Mexican border), which is located between Brownsville and McAllen (each of which is 4-5 times larger and has several hospitals). Knapp Medical Center has no competitors with 0-5 miles, one competitor within 5-15 miles (in McAllen) and 6 additional competitors within 15 - 25 miles (in both McAllen and Brownsville). There are $4^7 = 16384$ configurations of all facilities, tracking the identities of all hospitals individually, but only $\binom{0+4-1}{0}\binom{1+4-1}{1}\binom{6+4-1}{6} = 336$ different configurations of the state when firms are treated as symmetric, multiplied by 4, for 3 possible levels and an exit state.

[1] See the "Stars and Bars" combinatoric article on Wikipedia or [40]

I ignore all competitors in Mexico, which is without serious consequence, since few (if any) US citizens will cross the border to give birth in Mexico. The reverse is also true: the fraction of patients in Mexico who cross the border to give birth in US hospitals is quite small as a fraction of the total. In principle, it would be useful to know where they live in Mexico (their distances from hospitals in the US), how long it takes to cross the border (which is highly variable, even conditional on an hour of the day and season of the year, somewhat unpredictable, and measured in hours, not minutes), whether they cross by foot or driving, and how they value the neonatal intensive care services in US hospitals vs. their Mexican competitors. But the fraction of such patients is small in all hospitals along the border, with the possible exception of a single hospital in El Paso where in some years about one third of all births in this single hospital are to women with addresses in Mexico.

What makes the computation costly in terms of time is updating individual utility for each consumer for each of these firms. That is, I suppose that all consumers are aware of the level of each firm at the time when they make their decisions, so firms can expect that investments or divestments will change. When the aggregate state changes (i.e., when any firm is at a different level), then the deterministic component of utility must be updated for every consumer in the marketplace. Thus, the expected utility of going to each hospital must be updated at each location (zip code) which has that hospital as an option. Depending on the distances and levels, the number of aggregate states will generally be fewer than the number of configurations of levels in each possible facility.

For these markets, the value of only one state is updated each iteration. A single market configuration is chosen for an update randomly, where the probabilities are set according to the values computed for those states at earlier iterations of the algorithm. The values of all potential configurations are enumerated and initialized to some positive number, and then the transition to the next state is randomized, with probabilities weighted according to the values assigned to each state. The important trade-off is to assign those initial weights high enough to encourage exploration of the state space, but not so large that convergence never occurs. This method is well-described in both [86] and [29].

To judge convergence, I follow [29] and [41]. Convergence is measured at a subset of the states visited in the last million steps of the algorithm. The convergence test approximates the continuation value at each state visited in the last million iterations by drawing $K$ possible continuation locations from each state reached. This is the most computationally-intensive part of the approximation procedure, since for each of $M$ states visited, $K$ draws need to be made to compute the estimated continuation value. The cost of this computation increases rapidly in the number of states visited recently. For that reason, following [29] I only check convergence every million iterations or so.

The very largest markets, for example hospitals located in Houston or located between Dallas and Fort Worth have around 30 other facilities within 25 miles. The full market-configuration space in this case has about $4^30 = 2^{60} \approx 1e18$ elements. The size of the state space for the firm with the largest number of competitors among all firms is $\binom{9+4-1}{9}\binom{11+4-1}{11}\binom{13+4-1}{13} \times 4 \approx 180,000,000$. The cost of updating deterministic utilities for state spaces this large to compute demand are currently prohibitive. For that reason, I am not currently able to compute the solution to the dynamic program for a subset of firms.

# Bibliography

[1] Nikhil Agarwal and Paulo Somaini. Demand analysis using strategic reports: An application to school choice mechanism. *Econometrica*, 2017.

[2] Agency for Healthcare Administration - Certificate of Need Program Office. Florida hospital bed need projections and service utilization by service district. https://ahca.myflorida.com/m

January 2015. Last Accessed 09 11 2017.

[3] James H Albert and Siddhartha Chib. Bayesian analysis of binary and polychotomous response data. *Journal of the American Statistical Association*, 88:669–679, 1993.

[4] American Academy of Pediatrics - Committee on Fetus and Newborn. Levels of neonatal care. *Pediatrics*, 114:1341–1347, 2005.

[5] Simon P Anderson, Andre de Palma, and Jacques-Francois Thisse. *Discrete Choice Theory of Product Differentiation*. MIT Press, Cambridge, MA, 1992.

[6] Susan Athey and Armin Schmutzler. Investment and market dominance. *The RAND Journal of Economics*, 32:1–26, 2001.

[7] Mary Ellen Avery. A 50-year overview of perinatal medicine. *Early Human Development*, 29:43–50, 1992.

[8] Mike Baiocchi, Dylan Small, Scott Lorch, and Paul R. Rosenbaum. Building a stronger instrument in an observational study of perinatal care for premature infants. *Journal*

*of the American Statistical Association*, 45:1285–1296, 2010.

[9] Pat Bajari, Lanier Benkard, and Jonathan Levin. Estimating dynamic models of imperfect competition. *Econometrica*, 75:1331–1370, 2007.

[10] Pat Bajari, Han Hong, and Denis Nekipelov. Game theory and econometrics: A survey of some recent research. University of Minnesota Working Paper, 2010.

[11] Jeffrey P Baker. *The Machine in the Nursery*. The Johns Hopkins University Press, Baltimore, MD, 1996.

[12] Laurence Baker, Kate Bundorf, and Daniel Kessler. Does multispecialty practice enhance physician market power. NBER Working Paper, 2017.

[13] Laurence Baker and Ciaran Phibbs. Managed care, technology adoption and health care: The adoption of neonatal intensive care. *The RAND Journal of Economics*, 33:524–548, 2002.

[14] Wanda Barfield, Denise D'Angelo, Rachel Moon, Michael Lu, Betty Wong, and John Iskander. Public health approaches to reducing u.s. infant mortality. *CDC Grand Rounds*, 62(31):625–628, August 9 2013. Last Accessed 08 02 2016.

[15] Austin Bean. Inefficient technology investment: Competition, mortality and neonatal intensive care. UT-Austin Dept. of Economics Working Paper, 2017.

[16] Austin Bean. Volume-outcome effects in texas neonatal intensive care. UT-Austin Dept. of Economics Working Paper, 2017.

[17] C. Lanier Benkard. Learning and forgetting: The dynamics of airplane production. *American Economic Review*, 90:1034–1054, 2000.

[18] Steven Berry, Alon Eizenberg, and Joel Waldfogel. Optimal product variety in radio markets. NBER Working Paper, 2015.

[19] Steven Berry and Joel Waldfogel. Free entry and social inefficiency in radio broadcasting. *RAND Journal of Economics*, 30:397–420, 1999.

[20] David Besanko, Ulrich Doraszelski, and Yaroslav Kryukov. How efficient is dynamic competition? the case of price as an investment. NBER Working Paper, 2017.

[21] William Brangham. How a Coney Island sideshow advanced medicine for premature babies. http://www.pbs.org/newshour/updates/coney-island-sideshow-advanced-medicine-premature-babies/, July 21 2015. Last Accessed 08 02 2016.

[22] Steve Brooks, Andrew Gelman, Galin Jones, and Xiao-Li Meng. *Handbook of Markov Chain Monte Carlo*. CRC Press, Boca Raton, FL, 2011.

[23] Luis M. B. Cabral and Michael H. Riordan. The learning curve, market dominance and predatory pricing. *Econometrica*, 11:1115–1140, 2013.

[24] Cory Capps, David Dranove, and Mark Satterthwaite. Competition and market power in option demand markets. *RAND Journal of Economics*, 34:737–763, 2003.

[25] Manuel RG Carrapato, Ana Azevedo, Joana Rodrigues, and Fatima Fonseca. Thirty years of perinatal care in portugal. *Journal of Medical and Health Informatics*, 62:1–5, 1994.

[26] Victor Chernozhukov and Han Hong. An mcmc approach to classical estimation. *Journal of Econometrics*, 115:293–346, 2003.

[27] Siddhartha Chib. Markov chain monte carlo methods: Computation and inference. In James Heckman and Edward Leamer, editors, *Handbook of Econometrics, Volume 5*, pages 3569–3649. Elsevier, 2001.

[28] Javier Cifuentes, Janet Bronstein, Ciaran S Phibbs, Waldemar Carlo, Susan Schmitt, and Roderic Phibbs. Mortality in low birth weight infants according to level of neonatal care at hospital of birth. *The New England Journal of Medicine*, 356:2165–2175, 2007.

[29] Allan Collard-Wexler. Demand fluctuations in the ready-mix concrete industry. *Econometrica*, 81:1003–1037, 2013.

[30] Zack Cooper, Stuart Craig, Martin Gaynor, and John Van Reenen. The price ain't right? hospital prices and health spending on the privately insured. Working Paper, 2015.

[31] David Cutler, Robert Huckman, and Jonathan Kolstad. Input constraints and the efficiency of entry: Lessons from cardiac surgery. *American Economic Journal*, 2:51–76, 2010.

[32] David Cutler and Ellen Meara. The technology of birth: Is it worth it? pages 33–68, 2000.

[33] Eric Darr, Linda Argote, and Dennis Epple. The acquisition, transfer and depreciation of knowledge in service organizations: Productivity in franchises. *Managment Science*, 41:1750–1762, 1995.

[34] Partha Dasgupta and Joseph Stiglitz. Learning-by-doing, market structure and trade policies. *Oxford Economic Papers*, 40:246–268, 1988.

[35] Guy David and Tanguy Brachet. On the determinants of organizational forgetting. *American Economic Journal: Microeconomics*, 3:100–123, 2011.

[36] Ulrich Doraszelski and Mark Satterthwaite. Computable markov perfect industry dynamics. *RAND Journal of Economics*, 41:215–243, 2010.

[37] David Dranove and Mark Satterthwaite. The industrial organization of health care markets. In Anthony Cuyler and Joseph Newhouse, editors, *Handbook of Health Economics, Volume 1B*, pages 1093–1139. Elsevier, 2000.

[38] David Dranove, Mark Shanley, and Carol Simon. Is hospital competition wasteful? *RAND Journal of Economics*, 23:247–262, 1992.

[39] Richard Ericson and Ariel Pakes. Estimating dynamic models of imperfect competition. *Review of Economic Studies*, 62:53–82, 1995.

[40] William Feller. *Introduction to Probability Theory and its Applications, Vol. 1.* Wiley, New York, 1968.

[41] Chaim Fershtman and Ariel Pakes. Dynamic games with asymmetric information: A framework for empirical work. *Quarterly Journal of Economics*, pages 1611–1661, 2012.

[42] Seth Freedman. The effect of deregionalization on health outcomes: Evidence from neonatal intensive care. Working Paper, 2012.

[43] Seth Freedman. Capacity and utilization in health care: The effect of empty beds on neonatal intensive care admission. *American Economic Journal: Economic Policy*, 8:154–185, 2016.

[44] Martin Gaynor, Harald Seider, and William Vogt. Volume-outcome and antitrust in us health care markets. Working Paper, 2004.

[45] Martin Gaynor, Harald Seider, and William Vogt. The volume outcome effect, scale economies and learning by doing. *American Economic Review: Papers and Proceedings*, 95:243–247, 2005.

[46] Martin Gaynor and Robert Town. Competition in health care markets. In Mark Pauly, Thomas McGuire, and Pedro Barros, editors, *Handbook of Health Economics, Volume 2*, pages 499–639. Elsevier, 2012.

[47] Martin Gaynor and William B Vogt. Antitrust and competition in health care markets. In Anthony Cuyler and Joseph Newhouse, editors, *Handbook of Health Economics, Volume 1B*, pages 1405–1487. Elsevier, 2000.

[48] Andrew Gelman, John Carlin, Hal Stern, David Dunson, Aki Vehtari, and Donald Rubin. *Bayesian Data Analysis, 3rd Edition*. CRC Press, Boca Raton, FL, 2014.

[49] John Geweke and Michael Keane. Computationally intensive methods for integration in economics. In James Heckman and Edward Leamer, editors, *Handbook of Econometrics, Volume 5*, pages 3465–3564. Elsevier, 2001.

[50] John Geweke, Michael Keane, and David Runkle. Alternative computational approaches to inference in the multinomial probit model. *Review of Economics and Statistics*, 76:609–632, 1994.

[51] Edward Glaeser, Joseph Gyourko, and Raven Saks. Why have housing prices gone up. *American Economic Review*, 95:329–333, 2005.

[52] Edward Glaeser, Joseph Gyourko, and Raven Saks. Why is manhattan so expensive. *Journal of Law and Economics*, 48:331–369, 2005.

[53] Gautam Gowrisankaran, John Geweke, and Robert Town. Bayesian inference for quality in a selection model. *Econometrica*, 71:1215–1238, 2003.

[54] Gautam Gowrisankaran, Vivian Ho, and Robert Town. Causality, learning and forgetting in surgery. Working Paper, 2006.

[55] Gautam Gowrisankaran, Aviv Nevo, and Robert Town. Mergers when prices are negotiated: Evidence from the hospital industry. *American Economic Review*, 105:172–203, 2015.

[56] Gautam Gowrisankaran and Robert Town. Dynamic equilibrium in the hospital industry. *Journal of Economics and Management Strategy*, 6:45–74, 1997.

[57] Paul Grieco and Ryan McDevitt. Productivity and quality in health care: Evidence from the dialysis industry. *Review of Economic Studies*, 84:1071–1105, 2017.

[58] Susan Haber, Heather Beil, Walter Adamche, Peter Amico, Christopher Beadles, Olivia Berzin, Maggie Cole-Beebe, Jerry Cromwell, Leslie Greenwald, Konny Kim, Marisa

Morrison, Heather Pearson, and Alton Wright. *Evaluation of the Maryland All-payer Model: First Annual Report*. Centers for Medicare and Medicaid Services, Washington, DC, 2016.

[59] Ethan Halm, Clara Lee, and Mark R Chassin. Is volume related to outcome in health care. *Annals of Internal Medicine*, 1437:511–520, 2002.

[60] Gunther Heller, Douglas Richardson, Rainer Schnell, Bjorn Misselwitz, Wolfgang Kunzel, and Stephan Schmidt. Are we regionalized enough? early neonatal deaths in low-risk births by the size of delivery units in hesse, germany, 1990 - 1999. *International Journal of Epidemiology*, 31:1061–68, 2002.

[61] Corinna Hentschker and Roman Mennicken. The volume-outcome relationship and minimum volume standards: Empirical evidence for germany. *Health Economics*, 24:644–658, 2015.

[62] Kate Ho and Ariel Pakes. Hospital choices, hospital prices, and financial incentives to physicians. Working Paper, 2014.

[63] Vivian Ho, Robert Town, and Martin Heslin. Regionalization versus competition in complex cancer surgery. James Baker Institute at Rice University Working Paper, 2007.

[64] Jason Hockenberry and Lorens Helmchen. The nature of surgeon human capital depreciation. NBER Working Paper, 2014.

[65] Scott Holmstrom and Ciaran Phibbs. Regionalization and mortality in neonatal intensive care. *Pediatric Clinics of North America*, 56:617–630, 2009.

[66] Jeffrey Horbar, Gary Badger, Joseph Carpenter, Avroy Fanaroff, Sarah Kilpatrick, Meena LaCorte, Roderic Phibbs, and Roger Soll. Trends in mortality and morbidity for very low birth weight infants, 1991 - 1999. *Pediatrics*, 110:143–151, 2002.

[67] Embry Howell, Douglas Richardson, Paul Ginsburg, and Barbara Foot. Deregionalization of neonatal intensive care in urban areas. *American Journal of Public Health*, 92:119 – 124, 2002.

[68] Daniel Kessler and Mark McClellan. Is hospital competition socially wasteful? *The Quarterly Journal of Economics*, 115:577–615, 2000.

[69] Woohyeon Kim, Stephen Wolff, and Vivian Ho. Measuring the volume outcome relationship in complex hospital surgery. *Applied Health Economics and Health Policy*, 14:453–464, 2016.

[70] Morris Kleiner and Alan Krueger. Analyzing the extent and influence of occupational licensing on the labor market. *Journal of Labor Economics*, 31:S173–S202, 2013.

[71] Xiang-Yong Kong, Xiu-Xiang Liu, Xiao-Yang Hong, Jing Liu, Qiu-Ping Li, and Zhi-Chun Feng. Improved outcomes of transported neonates in beijing: The impact of strategic changes in perinatal and regional neonatal transport network services. *World Journal of Pediatrics*, 3:251–255, 2014.

[72] D J Mandell and M Kormondy. *2015 Healthy Texas Babies: Data Book.* Division for Family and Community Health Services, Texas Department of State Health Services, Austin, TX, 2015.

[73] N. Gregory Mankiw and Michael D Whinston. Free entry and social inefficiency. *The RAND Journal of Economics*, 17:48–58, 1986.

[74] March of Dimes/National Perinatal Information Center. Special care nursery admissions. https://www.marchofdimes.org/peristats/pdfdocs/nicusummaryfinal.pdf, 2011. Last Accessed 08 26 2017.

[75] Robert McCulloch and Peter Rossi. An exact likelihood analysis of the multinomial probit model. *Journal of Econometrics*, 64:207–240, 1994.

[76] Roos Mesman, Gert Westert, Bart J M M M Berden, and Marjan Faber. Why do high-volume hospitals achieve better outcomes? *Health Policy*, 119:1055–1067, 2015.

[77] Stephen Morris, Rachel Hunter, Angus Ramsey, Ruth Boarden, Christopher McKevitt, Catherine Perry, Nanik Pursani, Anthony Rudd, Lee Schwamm, Simon Turner, Pippa Tyrrell, Charles Wolfe, and Naomi Fulop. Impact of centralising acute stroke services in english metropolitan areas on mortality and length of hospital say: Difference-in-differences analysis. *British Medical Journal*, August 2014.

[78] National Conference of State Legislatures. Certificate of need - state laws. http://www.ncsl.org/resea
certificate-of-need-state-laws.aspx, August 2016. Last Accessed 09 19 2017.

[79] National Health Planning and Resource Development Act of 1974. http://uscode.house.gov/statutes/
January 1975. Last Accessed 09 19 2017.

[80] Maria Teresa Neto. Perinatal care in portugal: Effects of 15 years of a regionalized system. *Acta Paediatrica*, 95:1349 – 1352, 2006.

[81] Maria Teresa Neto. Regionalisation of perinatal care in portugal: Why and how it was accomplished. http://repositorio.chlc.min-saude.pt/bitstream/10400.17/1103/1/ap_273.pdf, 2011. Last Accessed 11 10 2017.

[82] New York State Department of Health. New York State Health Profiles. https://profiles.health.ny.go
Last Accessed 09 21 2017.

[83] Yien-Lan Nguyen, David Wallace, Youri Yourdanov, Ludovic Trinquart, Josefin Blomkvist, Derek Angus, Jeremy Kahn, Philippe Ravaud, and Bertrand Guidet. The volume outcome relationship in critical care: A systematic review and meta-analysis. *Chest*, 148:79–92, 2015.

[84] NPR. Babies On Display: When A Hospital Couldn't Save Them, A Sideshow Did. http://www.npr.org/2015/07/10/421239869/babies-on-display-when-a-hospital-couldnt-save-them-a-sideshow-did, July 10 2015. Last Accessed 08 02 2016.

[85] Ariel Pakes and Paul McGuire. Computing markov-perfect nash equilibria: Numerical implications of a dynamic differentiated product model. *RAND Journal of Economics*, 25:555–589, 1994.

[86] Ariel Pakes and Paul McGuire. Stochastic algorithms, symmetric markov perfect equilibrium, and the 'curse' of dimensionality. *Econometrica*, 69:1261–1281, 2001.

[87] Martin Pesendorfer and Philipp Schmidt-Dengler. Asymptotic least squares estimators for dynamic games. *Review of Economic Studies*, 75:901–928, 2008.

[88] Ciaran S Phibbs, Laurence C. Baker, Aaron B. Caughey, Beate Danielsen, Susan Schmitt, and Roderic Phibbs. Level and volume of neonatal intensive care and mor-

tality in very-low-birth-weight infants. *New England Journal of Medicine*, 356:2165–2175, 2007.

[89] Ciaran S Phibbs and Susan K Schmitt. Estimates of the cost and length of stay changes that can be attributed to one-week increases in gestational age for premature infants. *Early Human Development*, 82:85–95, 2006.

[90] Michael Pollak. The Incubated Babies of the Coney Island Boardwalk. *The New York Times*, July 31 2015. Last Accessed 08 02 2016.

[91] Warren B Powell. *Approximate Dynamic Programming*. Wiley, Hoboken, NJ, 2011.

[92] Subramanian Ramanarayan. Does practice make perfect: An empirical analysis of learning by doing in cardiac surgery. Working Paper, 2006.

[93] Christian P Robert and George Casella. *Monte Carlo Statistical Methods*. Springer, New York, NY, 2004.

[94] Peter Rossi, Greg Allenby, and Peter McCulloch. *Bayesian Statistics and Marketing*. Wiley, New York, NY, 2005.

[95] Stephen P Ryan. The costs of environmental regulation in a concentrated industry. *Econometrica*, 80:1019–1061, 2012.

[96] David S Salkever. Regulation of prices and investment in hospitals in the united states. In Anthony Cuyler and Joseph Newhouse, editors, *Handbook of Health Economics, Volume 1B*, pages 1489–1535. Elsevier, 2000.

[97] Philipp Schmidt-Dengler. The timing of new technology adoption: The case of mri. Working Paper, 2006.

[98] Andrew Sfekas. Learning, forgetting and hospital quality: An empirical analysis of cardiac procedures in maryland and arizona. *Health Economics*, 18:697–711, 2009.

[99] Daniel Sherman. The effect of state certificate of need laws on hospital costs: An economic policy analysis. Staff Report of the Bureau of Economics - Federal Trade Commission, 1988.

[100] James C Spall. *Introduction to Stochastic Search and Optimization: Estimation, Simulation and Control*. Wiley, Hoboken, NJ, 2003.

[101] Harry Straight. ORMC Vying for Deltona Spot. *The Orlando Sentinel*, January 30 1992. Last Accessed 03 12 2016.

[102] Abigail Tay. Assessing competition in hospital care markets: The importance of accounting for quality differentiation. *RAND Journal of Economics*, 34:786–814, 2003.

[103] Texas Dept. of State Health Statistics. Table 1 Resident Births and Deaths, Texas. https://www.dshs.texas.gov/chs/vstat/vs13/t01.aspx, July 31 2015. Last Accessed 08 17 2016.

[104] Texas Dept. of State Health Statistics, Center for Health Statistics - Hospital Survey Unit. Annual survey of hospitals. Texas Department of State Health Services/American Hospital Association, 1990 - 2012.

[105] Texas Health and Human Services Commission. Fy 2016 urban hospital prospective standard dollar amount. https://www.hhsc.state.tx.us/rad/hospital-svcs/inpatient.shtml, January 2016. Last Accessed 03 12 2016.

[106] Texas Health and Human Services Commission. Texas APR-DRG grouper current version. https://www.hhsc.state.tx.us/rad/hospital-svcs/inpatient.shtml, January 2016. Last Accessed 03 12 2016.

[107] Peter Thompson. How much did liberty shipbuilders learn? new evidence for an old case study. *Journal of Political Economy*, 109:103–137, 2001.

[108] Peter Thompson. How much did liberty shipbuilders forget? *Management Science*, 53:908–918, 2007.

[109] Peter Thompson. Learning by doing. In Bronwyn Hall and Nathan Rosenberg, editors, *Handbook of the Economics of Technical Change*, pages 1–57. Elsevier, 2009.

[110] Rebecca Achee Thornton and Peter Thompson. Learning from experience and learning from others: An exploration of learning and spillovers in wartime shipbuilding. *American Economic Review*, 91:1350–1368, 2001.

[111] Robert Town and Gregory Vistnes. Hospital competition in hmo networks. *Journal of Health Economics*, 20:733–753, 2001.

[112] Kenneth Train. *Discrete Choice Methods with Simulation.* Cambridge, New York, 2009.

[113] TX Department of State Health Services. Mortality narrative 2013. http://www.dshs.state.tx.us/chs
September 2015. Last Accessed 03 12 2016.

[114] US Court of Appeals, 11th Circuit. King Memorial Hospital and Florida Hospital Group v. FL Department of Health and Rehabilitative Services. 767 F.2d 1508 (1985), 1985.

[115] US Department of Health and Human Services - Health Resources and Services Administration. National outcome measures. https://mchb.tvisdata.hrsa.gov/PrioritiesAndMeasures/Nati
2013. Last Accessed 07 25 2016.

[116] US Department of Justice and the Federal Trade Commission. *A Dose of Competition*. US Government Printing Office, Washington, DC, 2004.

[117] W. Kip Viscusi and Joseph Aldy. The value of a statistical life: A critical review of market estimates throughout the world. *Journal of Risk and Insurance*, 27, 2003.

[118] Tonia J Wood. Records appraisal report report - texas health facilities commission. https://www.tsl.texas.gov/arc/appraisal/healthfacilities.html, September 1999. Last Accessed 08 12 2016.